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Industrial Electrical Engineering and Automation

Battery profit optimization

A study on when to end a battery`s first life, and begin its second life

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A study on when to end a battery's first life, and begin its second life

by Ebba Helfer

LUND UNIVERSITY

Thesis for the degree of Master of Science

Thesis advisors: Prof. Mats Alaküla

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Supervisor at the Division of Industrial Electrical Engineering was Professor Mats Alakühla. Deputy supervisor at the Division of Energy Sciences was Senior Lecturer Martin Andersson. Examiner at Lund University was Professor Olof Samuelsson.

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Contents

Nomenclature

EV	Electric Vehicle	
BEV	Battery Electric Vehicle	
$BESS$	Battery Energy Storage System	
ESS	Energy Storage System	
SoC	State of Charge	[%]
SoH	State of Health	[%]
DoD	Depth of Discharge	[%]
BoL	Beginning of Life	
EoL	End of Life	
LFP	Lithium Iron Phosphate	
SvK	Svenska Kraftnät	
NoC	Number of Cycles	
$1st\ life$	Battery inside an electric truck	
$2nd\ life$	Battery connected to the grid	
TSO	Transmission System Operator	
TCO	Total Cost of Ownership	
$TaaS$	Transport as a Service	
BMS	Battery Management System	

$BTMS$ Battery Thermal Management System

$FCR-D$ Frequency Containment Reserve - Disturbance

$aFRR$ Automatic Frequency Restoration Reserve

$FCR-N$ Frequency Containment Reserve - Normal

Sammanfattning

Inom en snar framtid kommer en ny marknad av 2nd life batterier bildas, då dessa inte längre är lämpliga att använda i elbilar och därför måste ersättas. Detta beror på deras försämrade förmåga att lagra energi, efter ett antal år av användning, på grund av två huvudsakliga åldringsmekanismer; cyklingsåldring och kalenderåldring. Dessa försämrade batterier kan däremot komma till god användning som batteri energilagringssystem, då energidensiteten inte är en lika viktig parameter för stationära applikationer.

Samtidigt som 2nd life batterimarknaden växer, befarar Svenska Kraftnät, som innehar balansansvaret i Sverige, att det kommer bli svårare att upprätthålla nätfrekvensen till den önskade nivån. Detta har lett till ökade investeringar i de så kallade balansmarknaderna, på vilka både stor- och småskaliga energi- och effektproducenter kan handla. Detta betyder att Svenska Kraftnät köper större volymer balanskraft, vilket skapar ett marknadsfönster för handel på balansmarknaderna med 2nd life batterier.

Ett batteris liv kan delas upp i ett första liv, inuti ett elfordon, och i ett andra liv, som en nätapplikation. För att intäktsmaximera under batteriets livslängd, uppstår frågan när batteriet ska tas ut från sitt första liv. För att svara på detta måste batteriets intjäningsförmåga under båda liven undersökas.

En modell implementerades som beräknade intjäningen under det första livet (baserat på industrins vinstmarginaler) och under den andra livet där intjäningen baserades på en implementerad handelsalgoritm. Resultaten visade att batterier har högre intjäningsförmåga, per kalenderdag, under dess andra liv i förhållande till dess första liv. Därtill, om 12 batterier, á 280 kWh initial energikapacitet, kopplas samman, bildar ett batteri energilager som handlar på balansmarknaderna, kan de, i bästa fall, tjäna upp till cirka 4.55 miljoner euro till slutet av batteriernas liv. I värsta fall, uppgår intjäningen till 1.1 miljoner euro.

Abstract

In the near future, a new market will form full of 2nd life batteries that are no longer suitable to use in electric vehicles. This since their capacity retention is too low after a few years of usage, as a consequence of two aging mechanisms; cycling aging and calendar aging. These batteries can be put into good use as battery energy storage systems, as the energy density is not as an important factor for stationary applications.

Simultaneously as the 2nd life battery market is growing, the Swedish transmission system operator Svenska Kraftnät, who is responsible for grid balancing, is fearing difficulties in maintaining the grid frequency at a satisfactory level. This has lead to increased investments in the balancing markets, where both large- and small-scale energy and power suppliers can trade. This means that Svenska Kraftnät are procuring larger volumes of balancing power, creating a market opportunity for trading on balancing markets with 2nd life battery energy storage systems.

The battery life can be divided into a 1st life, inside a vehicle, and a 2nd life, as a grid application. In order to maximize profit, the question regarding when to remove the batteries from the 1st life arises. In order to answer this question, both the 1st and 2nd life earnings potential need to be investigated.

A model was constructed which calculated the earnings in the 1st life (based on industry profit margins) and in the 2nd life based on an implemented trading algorithm. The results show that the batteries can earnings is higher, per calendar day, during the 2nd life than the 1st life. Additionally, if 12 truck batteries, with the initial energy capacity of 280 kWh, form a battery energy storage system which trades on the balancing markets, they can in the best case reach total earnings of approximately 4.55 million euros until end of life. The number corresponding to the worst case is approximately 1.1 million euros.

Acknowledgments

Going into the thesis work alone, I was fearing that I would be lacking in support and someone to brainstorm with. This was not the case, and therefore there are some individuals that I would like to highlight who made my autumn 2022, to the most educative, fun and rewarding semester of my degree.

First and foremost, I want to extend my deepest gratitude to Mats Alaküla, who in his role as my main supervisor, always challenged my approaches, supported me academically and rooted for me throughout my work. Without a doubt, this thesis would not have been possible without Mats and his engagement!

Secondly, I would like to thank Martin Andersson for his great help regarding how to navigate the very complicated energy and power markets.

I would also like to thank my friends and family, who have supported me and tirelessly listened to my ideas and questions throughout this process.

Ebba Helfer
Lund, January 2023

Chapter 1.

Introduction

Chapter 1 aims to provide a brief background on why the investigated thesis topic is relevant. In addition to that, the thesis questions, scope, method and delimitations are presented.

1.1. Background

In the close future, a new market of 2nd life batteries is expected to form, as the first 'large quantity' generation of electric vehicles will have reached their battery end of life (EoL), meaning that the old batteries no longer gives the desired range or performance and need to be replaced by new ones. It is assumed here that these batteries, that are taken out of the vehicle, still have a commercially meaningful capacity to store energy and convert power. This opens up for using 2nd life batteries in stationary applications, which is a vivid field of investigation. The vehicle fleet electrification has also spread to the commercial sector, meaning that more and more freight companies operate electric trucks entailing larger batteries in terms of kWh. Virtually, all of these battery electric trucks are equipped with lithium-ion batteries. The lithium-ion battery's state of health (SoH) strongly correlates with the battery cycling depth history. If the batteries undergo several deep discharge cycles, the lifetime in terms of number of cycles decreases in a similar manner as in figure 1.1, which is valid for a certain lithium-ion battery chemistry, namely lithium-iron-phosphate (LFP) batteries.

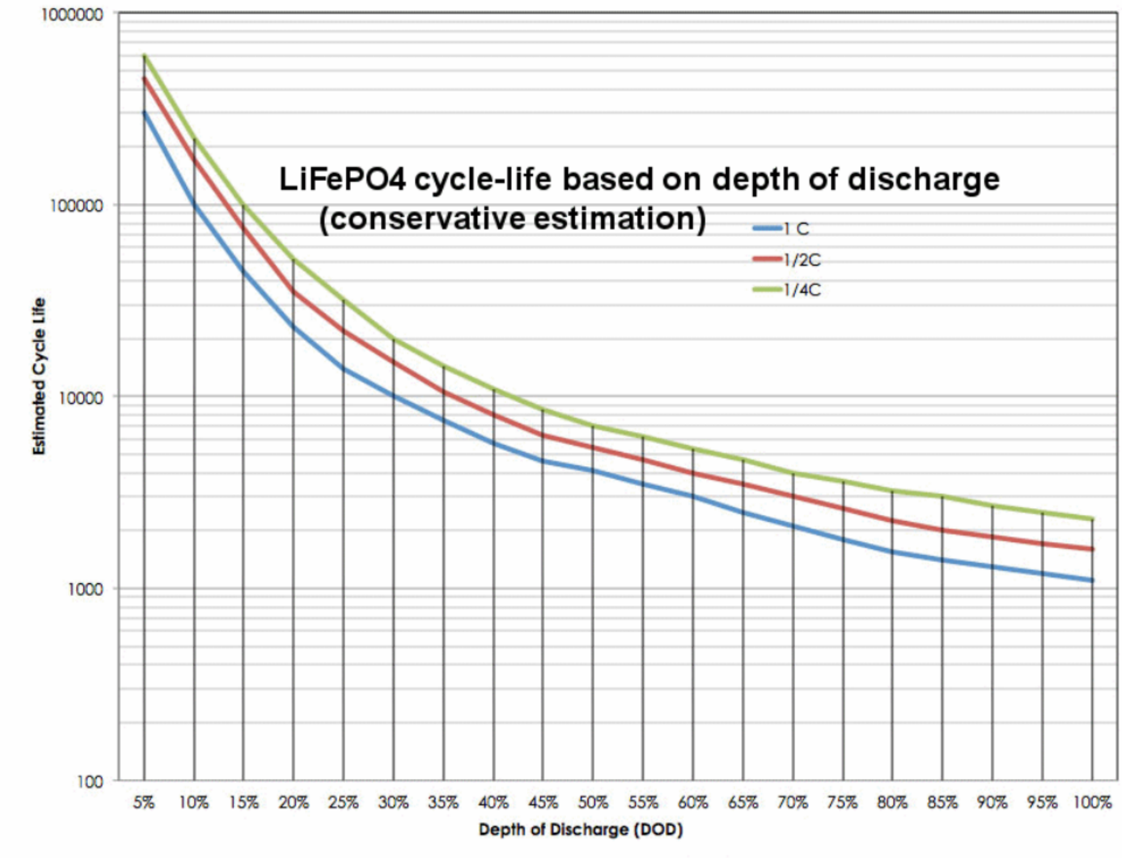


Figure 1.1.: Graph showing number of cycles for certain DoD's from SoH= 100% to 80% [1]. Note: This graph is not normalized to full cycle equivalents.

Today, many actors aim to replace vehicle batteries at a SoH of 80%, which is the industry standard [2]. This means that the energy capacity of the battery has dropped to a level where the daily range is reduced to 80% of the range of the new vehicle. This range is particularly important for commercial vehicles (CV) that exhaust the battery at least once, maybe twice, on a daily basis. However, there are some studies showing that it might be more beneficial, in terms of battery lifetime and total battery energy turnover, to end the battery's 1st life, inside an electric vehicle (EV), earlier than at $SoH = 80\%$, and begin its 2nd life, trading energy and power connected to the grid. Whilst connected to the grid, the specific energy density [kWh/kg] is not a key factor meaning that degraded, less high performing batteries are applicable in those situations.

After being removed from the trucks, the batteries can be connected together and form a battery energy storage system (BESS) and possibly participate on balancing and electricity markets. Since the BESS is connected to the grid, the cycle depth can be reduced and according to figure 1.1, this will entail a longer cycle life, due to the logarithmic scale, and possibly higher accumulated energy turnover.

To summarize, in the truck the battery works as a value creator since it can ship X tonnes of goods, Y kilometers. This transport as a service (TaaS) has a certain value. In contrast, the battery connected to the grid has another value due to the possibility of trading energy and power.

1.1.1. The Swedish balancing and electricity markets

In the current climate, with volatile energy prices and potentially planned power shortages, the Swedish transmission system operator (TSO), Svenska Kraftnät (SvK), is expanding the scope of the ancillary services, where the frequency-related services are traded on the balancing markets, allowing for bidders with smaller energy/power reserves [3]. This entails that smaller energy storage systems (ESS) operators can trade on these markets and the prognosis is that the investments in battery energy storage systems, or BESS, will increase the coming years [4].

1.1.2. Pre-study

Professor Mats Alakül̈a at Lund University performed a pre-study, which investigated when to take the batteries from transport services and instead use them for trading energy in the electric power grid, given repetitive DoD's in both its 1st and 2nd life, in order to maximize total energy turnover until EoL [5]. Alaküla introduces several concepts, which the model of this thesis are built and developed upon.

The study showed, amongst other things, that the maximal energy turnover is achieved if the 2nd life batteries are cycled in a shallow manner, given that the battery was cycled with repetitive DoD of 70% during its 1st life, as shown in figure 1.2.

The different colours in figure 1.2 represent the relative lifesplit, which is one of the concepts that is adapted from the pre-study in the thesis work. They represent how much of the battery life that is spent in the 1st and 2nd life respectively. A deeper explanation of this parameter is found in chapter 3.

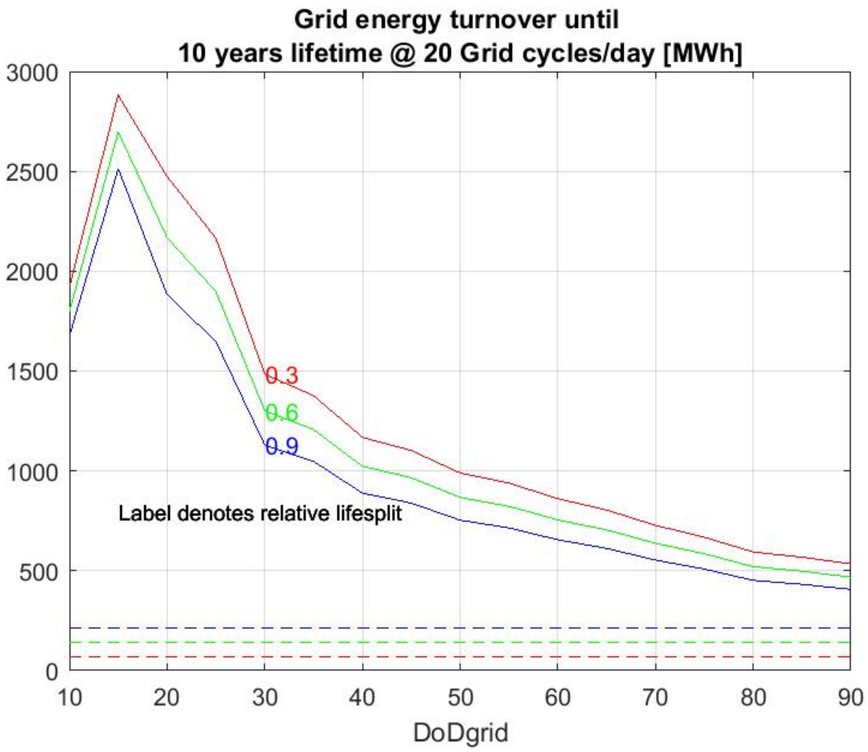


Figure 1.2.: Graph showing total energy turnover for a battery until EoL; limited by either calendar life or cycle life. The three colours represent the lifesplit vector, which is a concept that is further explained in chapter 3. The dashed lines represent the energy turnover during the battery's 1st life and the solid lines represent the energy turnover during the battery's 2nd life.

1.2. Objective

As the battery can provide different types of services in its 1st respectively 2nd life, the working hypothesis is that there should be a certain value of SoH when the battery should be taken out from the truck and begin its 2nd life, to optimize the battery usage profitability. Therefore, the main questions to investigate are:

> *(1)When should the traction batteries be taken out from the trucks, and...*
> *(2)How should these batteries be used in the grid...*
> *...to maximize economic profitability?*

In addition to the main questions, several sub questions need to be investigated such as:

- What is the monetary value of a battery energy cycle in a truck's 1st life?
- What is the monetary value of the same battery providing energy/power services during the battery's 2nd life?

- What is the cost of connecting the same battery to the grid, either as a battery pack directly from the vehicle or refurbished/rebuilt battery packs?

1.3. Method

The method largely consisted of model building in MATLAB, which was carried out step by step. First, a 1st life model was implemented, followed by an implementation of a 2nd life model, including the implementation of a trading algorithm. After the entire model was constructed, a script was created which performed a sensitivity analysis in the form of parameter sweeps. This model development is extensively described in the following chapters.

1.4. Delimitations

The study is solely focused on LFP batteries and does not take into consideration other battery chemistries. Additionally, regarding energy and power trading during the 2nd life, only the Swedish balancing market is available for trade and no further research has been conducted of other markets.

Lastly, several assumptions, which act as limitations for the study, are made in order to simplify the model. They are presented under chapter 3.

Chapter 2.

Theory

This chapter aims to provide basic theoretical background in order to facilitate understanding of the reasoning and assumptions made in chapter 3. First, an introduction of the electric freight market and battery use in commercial vehicles is presented. This is followed by some theory regarding battery technology, LFP batteries and their characteristics. Lastly, an explanation of certain energy and power markets is provided.

2.1. The electric freight market

The electric freight market is a relatively young market, where companies provide pure electric freight alternatives. The market is experiencing rapid growth, driven by regulations and the advantageous total cost of ownership (TCO) of electric trucks [6].

The traditional freight market, in general, is subject for low profit margins around 2 - 7% [7]. For sustainable freight alternatives, the prediction is that the profit margin is somewhat higher, around 5-15% [8].

2.1.1. Battery use in commercial electric vehicles

In general, batteries used in electric vehicles are carefully designed as they are heavy, meaning that their extra weight contributes to a larger energy consumption and reduce maximum payload. This is the battery oxymoron, as they constitute the vehicle's energy storage but at the same time drive up the energy consumption and reduce payload. Therefore, the batteries in vehicles are dimensioned as small as possible, as large as necessary for a given operating envelope. This is of greater importance for commercial vehicles, where there is an additional trade-off between the battery weight and the cargo weight. As a consequence of this and the battery size, the battery is usually cycled deeper in commercial vehicles than cars, with up to several deep cycles per day.

2.2. Battery technology

A battery cell is an electrochemical device which converts chemical energy to electrical energy during discharge and vice versa during charge. Battery cells can be connected in series/parallel forming battery modules. If these modules are assembled together, they form a battery pack. This is done to achieve desired levels of e.g. voltage and energy capacity. Battery packs are commonly used as the umbrella term for the ready ”battery” that is installed in e.g. vehicles, and usually contain a battery management system (BMS) and battery thermal management system (BTMS) [9].

Several battery packs can be assembled together and form a BESS (battery energy storage system). A BESS should be interpreted as a system that can be used separate from the vehicle application, e.g. connected to the electric power grid to perform power and energy services. This system can be made up of new or 2nd life batteries. When assembling a BESS, should it be made with 2nd life batteries, a health check of the batteries should be performed to ensure best possible performance. If several battery packs are connected in series, its maximal current will be limited by the battery pack with the lowest current limitation [10], and thereby the maximal power is also limited by the weakest link, given a certain voltage. This could be the case with batteries used differently during their 1st lives. Consequently, to avoid not using the batteries to their full potential, packs of equal characteristics should be assembled together.

There are several different battery chemistries on the market. Nevertheless, this thesis solely focuses on Lithium-iron-phosphate (LFP) batteries, as they are commonly used in electric trucks.

2.2.1. Lithium-iron-phosphate batteries

LFP batteries are a type of lithium-ion batteries, which popularity in EV’s has risen over the years as they possess high energy density, low self-discharge rate and long cycle life. As opposed to some other secondary battery types, lithium-ion batteries, such as the LFP battery, do not experience memory effect, which is beneficial in a 2nd life application with possible shallow cycling [11].

The cost of an LFP battery pack used in an vehicle application is around 100-200 Euro/kWh in 2022, which is a competitive price tag in comparison to other battery chemistries [12]. This also translates to the recycled value, as recycled LFP batteries are significantly worth less per kWh than other chemistries, see figure 2.1.

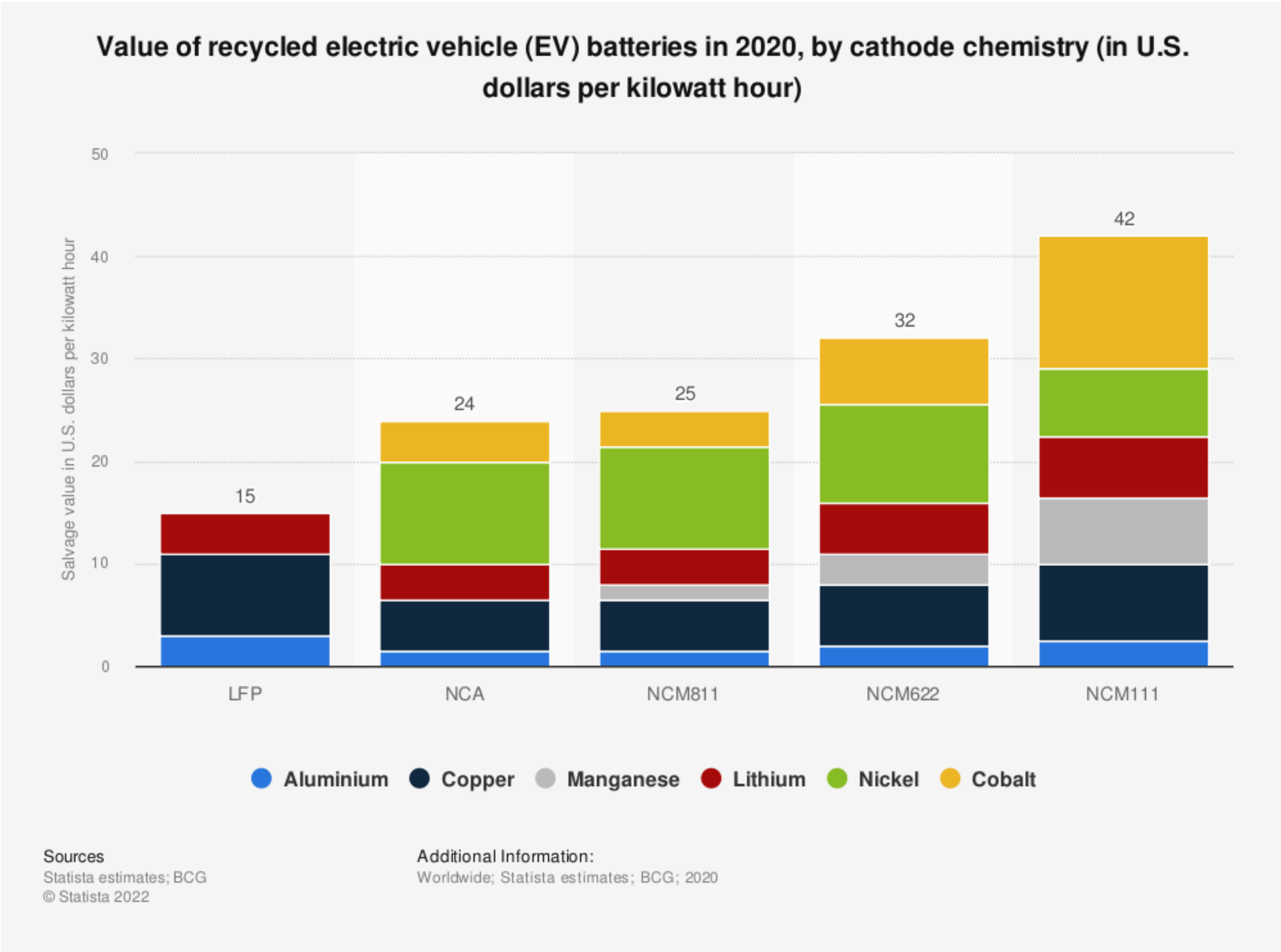


Figure 2.1.: Value of recycled EV batteries in 2020, by cathode material. [13]

2.2.2. Relevant characteristics

Battery Capacity: A measure of the maximum amount of stored energy usually expressed in kilowatt hours [kWh]. The battery capacity ($W_{initial}$) decreases over time due to cycle and calendar aging and is highest in the Beginning of Life (BoL).[14]

C-rate: A measure of how fast a battery is (dis)charged. If a fully charged battery with a capacity of 100 kWh is fully discharged in one hour, then the discharging rate is 1C - corresponding to 100 kW discharge power. If the same battery is charged in 30 minutes, the corresponding charge rate is C=2 or 200 kW charge power. The higher the C-rate during a (dis)charging cycle, the higher the battery wear in accordance to figure 1.1. The maximum charge rate for energy optimized batteries, most commonly used in EV's, is around 2-3 C. Batteries in hybrid electric vehicles are often power optimized, which allows for higher charge rates around 10 C [5].

SoC: State of Charge (SoC) is a measure of how much of the full battery capacity ($W_{initial}$) the battery contains at a certain point in time ($W_{remaining}$), see eq. 2.1. SoC is most commonly expressed in percentage [%][2].

$$SoC = \frac{W_{remaining}}{W_{initial}} \cdot 100\ [\%] \tag{2.1}$$

DoD: Depth of Discharge (DoD) is expressed as $DoD = 1 - SoC$ and is a relative measure of how much energy the battery has used, in comparison to the full battery capacity. DoD is commonly expressed in percentage [%] [2].

SoH: State of Health (SoH) is a measure of how much capacity reduction the battery has experienced [2]. It is calculated as the quotient between current capacity and the 'fresh' capacity the battery had at BoL, see eq. 2.2.

$$SoH = \frac{W_{current}}{W_{fresh}} \cdot 100\ [\%] \tag{2.2}$$

EoL: End of life is often defined as $SoH = 80\%$ for vehicle batteries. After $SoH = 80\%$ the degradation becomes more unpredictable and current manufacturers do not provide warranties beyond a certain SoH, here assumed to be 80%. However, this does not mean that the battery can no longer supply energy. Therefore, in this thesis, EoL in the battery's first life occurs at $SoH = 80\%$ and $SoH = 60\%$ in its second life, which is used in other literature [15], [16].

Energy and power density: Energy density is a measure that is useful when analyzing the trade-off between the battery capacity and the battery weight. Specific energy density is usually expressed in Wh/kg. Power density refers to the trade-off between available output power and battery weight and is expressed in W/kg. Figure 2.2 shows the different power vs. energy densities for some battery technologies. Lithium-ion batteries have high energy density and a power density compared to the other technologies, but the proportions between energy density and power density can be varied a lot with the battery design to adapt a specific battery to a specific application [17]. For stationary applications, the specific energy density [kWh/kg] is not as important as for batteries in vehicles due to the weight-capacity trade-off. With this in mind, the above extension of EoL at $SoH = 60\%$ is justified.

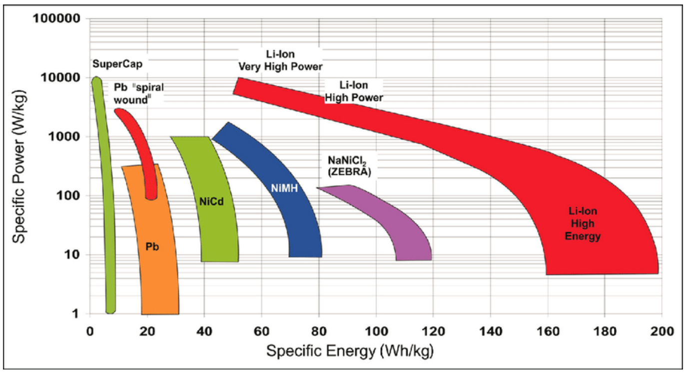


Figure 2.2.: Ragone plot showing the specific power vs. energy density for different battery technologies. [17]

Calendar life: The calendar life refers to how long the battery can be expected to function, disregarding cycle degradation [18]. Consequently, the limiting factor of a battery's life can either be calendar life or cycling life. The calendar life depends on the storage conditions, and benefits from low temperature storage.

2.2.3. Battery degradation

Battery degradation is an inevitable phenomenon as it is driven by two main factors which are cycle aging and calendar aging. Cycle aging occurs when the battery is in operations and is highly dependent under which conditions the cycling occurs, e.g. temperature, C-rate and DoD. Calendar aging occurs constantly but is also affected by the conditions under which the battery is stored. A battery that is stored with a $SoC = 80\%$ is expected to have a shorter calendar life than a battery stored at $SoC = 40\%$ [19]. For batteries in daily operations (with little storage time), the cycling aging occurs significantly faster, making it the dominating degradation factor. The studies of degradation mechanisms are outside of this thesis scope but can be found in e.g. [20].

As mentioned earlier, battery aging depends on several parameters. Nevertheless, a simple degradation model can be built upon reasoning from figure 1.1. If a battery has repetitive cycles with $DoD = 60\%$, the vehicle will have reached SoH=80% after approximately 3000 cycles (for 1C). The extension of this is that one cycle, with a $DoD = 60\%$, contributes to a degradation of $\frac{1}{3000}th$ of the aging from SoH=100% to SoH=80% ($\frac{1}{3000}th$ needs to be multiplied by 0.2 in order to represent degradation in the interval SoH=100% to SoH=0%). Therefore, for a charging cycle consisting of n subcycles, the total degradation can be calculated as eq. 2.3, where $Number\ of\ cycles_k$ represents the corresponding y-value of figure 1.1 for the DoD-value of each of the n subcycles. This way of modelling is supported in [21].

$$degradation = \sum_{k}^{n} \frac{1}{Number\ of\ cycles_k} \tag{2.3}$$

2.3. Energy and power markets

2.3.1. Battery energy storage systems

A BESS can alleviate strains on the power system, facilitate peak-shaving and function as a power back-up during shortages or outages [22]. Its importance is growing as more intermittent energy resources are integrated in the Swedish electricity mix [23].

The BESS economy and sustainability becomes interesting when considering the use of 2nd life batteries. If investing in 2nd life batteries, the initial battery cost could potentially be 30-70% lower than with new batteries, making investments in BESS more attractive [24]. As a result of a growing 2nd life market, the selling price for EV's could also be reduced [25], as a part of the battery value is allocated to the battery's 2nd life, creating a snowball effect leading to even lower prices of 2nd life batteries as the market saturates.

BESS' are assumed to constitute the vast majority of energy storage systems (ESS) in Sweden in the coming five years and the development of the market is assumed to be driven by the transport sector. By the end of 2022, it is forecasted that the Swedish power companies will have installed a BESS power capacity of the order 80-100 MW [4]. The number is uncertain as there are no official statistics concerning energy storage systems.

Figure 2.3.: A collaboration between Northvolt, Scania and EVBox, using a BESS in conjunction with heavy electric vehicle charging. [26]

Grid connection costs

If a BESS is to trade on the balancing markets, it needs to be connected to the grid which entails grid connection costs.

The grid connection cost differs, depending on which power company that operates the distribution grid. Table 2.1 shows a specific grid tariff of Vattenfall, a large Swedish power company, for a power rating contract called 'N3', which is applicable in region 'SOUTH' (see figure 2.4 for region description) and allows for high voltage connections which are suitable for BESS'. In addition to this, Vattenfall offers compensation for companies which provide the grid with electricity. The compensation is presented in table 2.2. [27]

Figure 2.4.: Map of Sweden showing Vattenfall's two different areas; område norr (area north) and område söder (area south) [27]

For both table 2.1 and 2.2, there are different fees/compensations for 'high load' and 'other time'. High load is defined as: Weekdays from 06.00-22.00 during the months of January, February, March, November and December [27].

Table 2.1.: Grid connection fees for Vattenfall N3 contract [27].

	N3	Unit
Fixed cost	2 400	SEK/month
Monthly power fee	27	SEK/kW, month
High load fee	55	SEK/kW, month
Transfer fee, high load	0.189	SEK/kWh
Transfer fee, other time	0.066	SEK/kWh

Table 2.2.: Energy production reimbursement for Vattenfall high voltage connections [27].

	High voltage connections	Unit
Power reimbursement, high load	54	SEK/kW, month
Energy reimbursement, high load	0.11	SEK/kWh
Energy reimbursement, other time	0.039	SEK/kWh

2.3.2. Balancing markets

Svenska Kraftnät (SvK) is the Swedish Authority of Electricity Contingency Planning and the Swedish transmission system operator (TSO). This means that SvK is the authority responsible for the national grid, balancing electricity production/consumption and ensuring grid stability in case of extreme strains [28].

Given recent events, current climate on European electricity markets and larger strains on the Swedish national grid, SvK are increasing their investments in ancillary services. An ancillary service is a frequency control service which help SvK contain the frequency around 50 Hz. If the frequency significantly deviates from 50 Hz, the grid stability is at risk and power outages are possible [29]. A BESS connected to the AC grid is connected via power electronic converters. These are very fast power controllers and ensure that the battery, with short notice (milliseconds), can change from a load (charging) to a source (discharging) [5]. This ability is here called a ”support service”.

The above mentioned investments are prospected to continue growing in the near future, as the market will see a higher degree of electrification and a larger share of integrated intermittent energy sources. Figure 2.5 shows the increasing trend and also which ancillary services, explained in the subsequent sections, that will experience rapid growth.

In general, electricity needs to be consumed the same moment as it is produced in order to maintain grid balance. However, trade-balance is generally not kept as production/consumption predictions often differ from reality. This generates the need of ancillary services that can accommodate for real-time grid status [29].

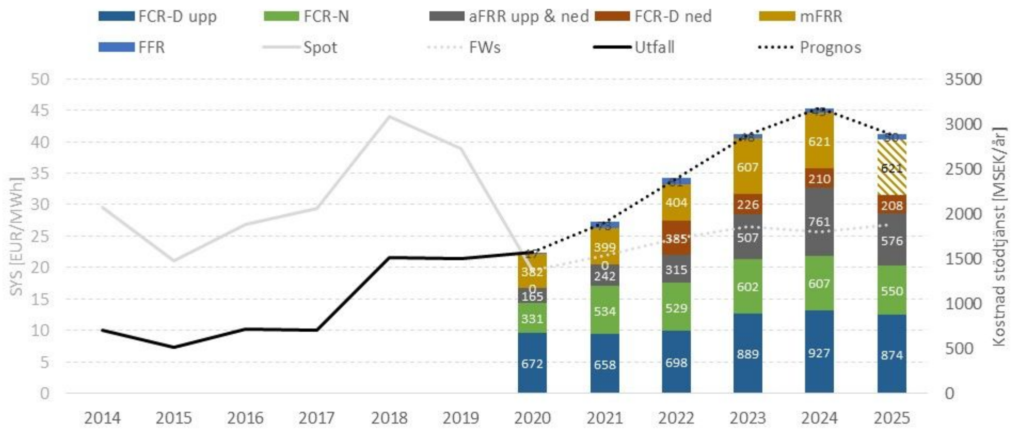


Figure 2.5.: SvK is increasing their investments in ancillary services, which is expected to peak 2024 [30].

Trading on the balancing markets

Each service is object for specific trading rules, which are described below under each service. However, the trading process can be somewhat generalized.

Sometime before (depending on the service) the service is needed, SvK collects bids from registered ancillary service suppliers. Each supplier submits a bid containing volume (in megawatts) and price. SvK then accept bids, from cheapest to most expensive, until they have reached the desired volume. When the time of delivery arrives, some of the accepted bids will be activated, meaning that they will supply the grid with the agreed, and activated, volume. At some hours, not all accepted bids will get activated, meaning that in some cases, the service provider can generate revenue without being called upon, and in the case of a BESS providing the service no battery wear will occur.

Below, an in-depth explanation of some ancillary services is provided. In chapter 3, a trading algorithm for the battery's 2nd life application is presented. The below explanation only regards the services which are included in the trading algorithm. For a quick overview, see table 2.3.

Some of the services only get reimbursed for their power capacity (hereafter referred to as capacity reimbursement), euro per megawatt, whilst other services receive capacity reimbursement plus an additional energy reimbursement at the time of activation. The energy reimbursement can be negative if the ancillary service is a down regulation, meaning that bidder receives energy.

aFRR

aFRR is the abbreviation for automatic frequency restoration reserve and is automatically activated when the frequency deviates from 50 Hz [31], meaning that it is activated nearly 100% of the time. It is an unsymmetrical product, meaning that aFRR bids are either up or down services [31]. Up regulation entails either increasing power production or decreasing consumption, whilst down regulation entails decreasing power production or increasing consumption. This can directly be compared to the corresponding functions of a BESS, i.e. charging/discharging.

SvK's demand for participants of the aFRR trade are the following [32]:

- Minimal bidding volume: 1 MW. Larger bids are multiples of 1 MW.
- Activation time: 100% within 5 minutes.
- Endurance: 1 hour.

Trading and pricing of aFRR

SvK procures the desired aFRR balance capacity one day before operations. At the moment of procurement, each accepted bid receives the capacity reimbursement which corresponds to the marginal price. The marginal price, in turn, corresponds to the highest accepted bid. If the bids are later activated, the suppliers receives an additional energy reimbursement which differs between up and down regulations [33]. In general, the total earnings potential for up-regulations are represented by capacity reimbursement plus energy reimbursement. For the case of down regulations, the earnings equals capacity reimbursement minus the energy reimbursement.

FCR-N

FCR-N, frequency containment reserve - normal, is activated when there are frequency deviations within the 'normal span' of operations, i.e. 49.90-50.10 Hz. It is a symmetrical product, meaning that a bidder on the FCR-N market needs to be able to accommodate for both up and down regulations [32]. According to a study conducted from 2015 to 2020, the grid frequency was within the FCR-N interval 98% of the time [3].

SvK's demand for participants of the FCR-N trade are the following [32]:

- Minimal bidding volume: 0.1 MW. Larger bids are multiples of 0.1 MW.
- Activation time: 63% within 1 minute and 100% within 3 minutes.
- Endurance: 1 hour.

Trading and pricing of FCR-N

The FCR-N services are procured either two or one day(s) before operations. At the time of trading, a bid get accepted or not. For all called bids, SvK pays out a capacity reimbursement [EUR/MW]. This reimbursement is paid regardless if the bid is activated or not at the given operation time. Additionally, if the bid is activated and it is an up-regulation, the bidder receives an energy reimbursement [EUR/MWh]. However, if the activated bid is a down-regulation, the bidder needs to pay SvK an energy reimbursement. In 2024, the capacity reimbursement will change from pay-as-bid to marginal price [3].

FCR-D

FCR-D, frequency containment reserve - disturbance, is automatically activated in cases of frequency deviations within the span 49.90-49.50 respectively 50.1-50.5. There are two type of FCR-D's, up and down. Which one is activated depends on if the frequency is too low respectively too high. The frequency deviations when FCR-D services are needed only occur 2% of the time [3]. At that point, other ancillary services are already activated for smaller frequency deviations and due to the activation time FCR-D, the bidders will only get activated between 40-55 % of the 2% when they are needed, which implies short periods of active time. This means that even if the power is high for a FCR-D service, the total energy transfer will be low.

SvK's demand for participants of the FCR-D up and down trade are the following[34] [35]:

- Minimal bidding volume: 0.1 MW. Larger bids are multiples of 0.1 MW.
- Activation time: 50% within 5 seconds and 100% within 30 seconds.
- Endurance: Minimum 20 minutes.

Trading and pricing of FCR-D

The FCR-D services are procured either two or one day before operations, with the majority traded two days before. In contrast to FCR-N, FCR-D services are only reimbursed for their power capacity (EUR/MW) and whether or not the bid gets activated does not effect the earnings for such a service. This can be explained by the short time frame in which the FCR-D services are activated, which results in low energy flows and negligible earnings or costs.

Summary of ancillary services

Table 2.3.: Characteristics for different ancillary services [3].

	FCR-N	FCR-D up	FCR-D down	aFRR
Symmetrical	Yes	No	No	No
Activation	Aut.	Aut.	Aut.	Aut.
Activation time	63% within 1 min 100% within 3 min.	50% within 5 s, 100% within 30 s.	50% within 5 s, 100% within 30 s.	100% within 2 min, (*100% within 5 min)
Endurance	1 h	20 min	20 min	1 h
Reimbursement	Power capacity and energy	Power capacity	Power capacity	Power capacity and energy
Statistics (percentage of time)	98%	1 %	1 %	100%

Other energy storage systems applicable for frequency trading

As shown in figure 2.5, there are several types of support services that are of interest for SvK. The main difference between the services are at which frequency they are activated. Additionally, the services are usually active during different time frames, making different types of ESS' suitable for different services. A mapping of suitable options is presented in table 2.4 [3]. It shows that batteries, together with gas turbines, are suitable for all current support services, making them a competitive choice when designing ESS'. This is partially due to batteries quick response time.

An extended description of this table can be found in the RISE report [3].

Table 2.4.: Table showing which ESS's are technically suitable for which support service. More information about the table can be found in the source. [3]

	FFR	FCR-N	FCR-D down	FCR-D up	aFRR	mFRR
PEM electrolysis	(Yes)	Yes	Yes	Yes	Yes	Yes
ALK electrolysis	No	(Yes)	(Yes)	(Yes)	Yes	Yes
SOEC electrolysis	No	No	No	No	Yes	Yes,
Battery	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Gas turbine	Yes	Yes	Yes	Yes	Yes	Yes
Fuel cell	No	Yes	Yes	Yes	Yes	Yes

2.3.3. Electricity markets

Electricity can be traded on the day-ahead and intraday markets. What differs the two, is at what point in time bidding occurs. Bids on the day-ahead market have to be submitted before 13.00 the day before delivery. However, there are some non-predictable fluctuations in both supply and demand, entailing that the markets need to accommodate these discrepancies, which is the role and purpose of the intraday market. On the intraday market, buyers and sellers can trade in real time, hour by hour [36].

Chapter 3.

Modelling and Simulation

This chapter aims to provide an overview of the thought process behind the modelling and simulations. To start, the simulation tools and strategy are presented. This is followed by a deep dive into the battery degradation model, which begins with an explanation and motivation of the different assumptions that were made. Thereafter, the 2nd life modelling and the trading algorithm, together with corresponding assumptions, are described in detail, as well as some comments regarding the algorithm's input data.

3.1. Simulation tools and methodology

The model is built in a MATLAB environment and is divided into three main sections which are *1st life battery modelling*, *2nd life battery modelling* and *Trading algorithm*.

In order to run the model, real data for a vehicle's SoC over time is needed, with a resolution of one minute. Before running the model, the vehicle's SoC data is processed so that all data points with missing values, due to errors during data collection, are populated with the SoC-value of the previous data point. Afterwards, the 1st life battery aging model is run and results in output data regarding battery degradation and earnings during 1st life. This data acts as input data for the 2nd life battery model, which allows the trading algorithm to decide how the battery will act on the balancing markets, entailing a certain battery cycling behaviour until EoL.

3.1.1. 1st life battery model

Applicable assumptions - 1st life

Battery size and type: The battery is assumed to be an LFP battery with an initial battery capacity of $W_{initial} = 280\ kWh$. Only a single battery is modelled in the 1st life.

Degradation: Degradation is assumed to be linearly, between certain SoH's, dependent on the energy cycling. More information regarding this can be found below under 'cycle weight'.

Cycle depth: All subcycles are assigned a corresponding DoD value in accordance to figure 1.1. These cycles are all assumed to start at $SoC = 100\%$, meaning that a real cycle that started at $SoC = 60\%$ and ended at $SoC = 40\%$, is regarded as a cycle that went from $SoC = 100\%$ to $SoC = 80\%$ [37]. This assumption was necessary as no other method regarding how to treat this was found. This assumption simplifies the model and affects the total expected lifetime of the battery.

Battery cost: The battery cost is assumed to represent 30% of the total procurement cost of an EV. This assumption indicates how much of the earnings in the 1st life that should be allocated to the battery [38], meaning that if a vehicle earns 100 euro per day, 30 euros are directly allocated, and belongs to, the battery.

Costs: The costs in the 1st life are assumed to correspond to the TCO, which covers the majority of all cost drivers, e.g. driver wages, degradation of hardware (not battery degradation), efficiency losses and electricity costs. The TCO is calculated for vehicles driven in Sweden, with Swedish wages, electricity prices, taxes etc. The TCO is also changed for the two different test vehicles as their load and driving pattern differ, resulting in different TCO's.

Earnings: 1st life earnings are assumed to be exclusively comprised of the profit margin. The profit margin is based on an article (see ref. [8]) which used machine learning models to predict profit margin for sustainable road freight transportation. Although the article gives no written value of the average profit margin, the assumption is that the profit margin is 5%, which seems to be the average of the accumulated results, which are presented in figures in the article. The TCO, adjusted with cost regarding battery degradation, is multiplied by the profit margin, resulting in the 1st life earnings.

Battery cost allocation: The battery is assumed to have a residual value of 10% at EoL [13]. The remaining 90% are allocated to the 1st respectively 2nd life, where the partition is assumed to be symmetrical with 45% assigned to each life. This assumption is justified as, theoretically, 20% degradation is allowed in both 1st (SoH=100% to 80%) and 2nd life (SoH=80% to 60%), implying the symmetrical partition.

Cycle weight: A cycle performed during the SoH interval 100-80% is assigned the weight of 1 [39]. Other weights, for other SoH intervals, will be discussed in the 2nd life modelling assumptions.

Temperature: Temperature plays one of the most important roles in battery degradation. However, temperature dependency is disregarded in the battery modelling under the assumption that the vehicles operate with well-functioning BTMS'.

1st life battery aging model

One of the main purposes of the battery aging model is to visualize how different charging cycles affects battery degradation during the 1st life. In order to create this test environment, a model is built which calculates the battery degradation in accordance to algorithm 1. Prior to entering algorithm 1, the rainflow algorithm (explained in appendix A) analyses the SOC-data, identifies all relevant full/half cycles and assigns them a DoD (which populates an *amplitudes* vector) and a value of 1 or 0.5 (full respectively half cycle). As figure 1.1, which provides the model with the 'number of cycles' and corresponding DoD's, only shows data for DoD's equal to, or larger than, 5%, the same limit is set in algorithm 1, neglecting more shallow cycles.

Algorithm 1 Algorithm for calculating battery degradation for input SoC-data

Number of cycles =
  $[3e5\ \ 1e5\ \ 25e3\ \ 1e4\ \ 5.9e3\ \ 4e3\ \ 2.9e3\ \ 2.1e3\ \ 1.5e3\ \ 1.2e3\ \ 1.01e3]$
DoD = [5 10 20 30 40 50 60 70 80 90 100]
while SoH > 0.8 **do**
  for $i = 1 : length(amplitudes)$ **do**
    if $amplitudes(i) \geq 5$ **then**
      $cycles$ = interpolate NumberofCycles on amplitudes(i) w.r.t. DoD
      $degradation = degradation + \frac{1}{cycles} \cdot 0.2$
    end if
  end for
end while
SoH = SoH - degradation

At the point of degradation calculation in algorithm 1, 1/cycles is multiplied by 0.2. This is done to calculate degradation within the interval 100-0% SoH, and not 100-80% SoH, which is the SoH-interval that figure 1.1 number of cycles is based upon.

Algorithm 1 is run until SoH has reached 80%. At that point, the total time in the 1st life is multiplied by the lifesplit vector, which indicates how much of the available 20% is spent in the 1st life. To clarify, if the lifesplit equals 50%, only 10% degradation is allowed in the 1st life, meaning that the battery is taken out at $SoH = 90\%$. The multiplication with the lifesplit vector allows for the transition of studying one case, to four cases. Figure 3.1 further shows the lifesplit concept.

Figure 3.1.: Figure illustrating the 'lifesplit' concept.

The lifesplit vector consists of four different values, meaning that the model is left with four cases, representing different time spent in the 1st life, resulting in different revenues and battery wears which later act as the input data for the 2nd life model. The lifesplit values were chosen with even intervals between them, with the exception of 0.2, which was chosen in order to investigate if something in the analysis significantly changed when the batteries were taken out very early during the 1st life. The lifesplit vector multiplication facilitates the analysis of *when to take out the battery from its 1st life*.

3.1.2. 2nd life battery model

In its 2nd life, the battery is assumed to be combined with other batteries, forming a BESS which trades on the Swedish balancing markets and the day-ahead market. Below follows a list of assumptions that were made to build the 2nd life model.

Applicable assumptions

BESS capacity: The battery used in the 1st life is assumed to be combined with eleven additional batteries, forming a BESS consisting of twelve vehicle batteries. The reason why twelve batteries are used to form the BESS is so that the trading algorithm can trade aFRR (which has a minimum bidding demand of 1 MW) with a reasonable DoD until EoL. At EoL, an aFRR trade during 1 hour (i.e. 1 MWh), roughly represents a DoD=50%. When fewer batteries were used, the earnings significantly decreased as aFRR trading was blocked frequently. Due to the previously mentioned lifesplit vector, the four BESS cases that are modelled begin their 2nd life with different SoH's, as they degraded more or less during the 1st life. In order to model the initial energy capacity of the combined BESS in the 2nd life, all input data from *1st life modelling* is multiplied by twelve, meaning that all twelve batteries in the same BESS have experienced the same 1st life.

Disassembly: When the battery is taken out from its first life, it is taken out in the form of battery packs and neither disassembled into modules nor cells. This cost is assumed to be 32 Euro/kWh in accordance to [38], and includes both labour and battery health checks. No data regarding the BESS assembling cost was found and is therefore left out of the analysis.

Costs: The costs of starting the battery's 2nd life includes disassembly costs and also investments in power electronics needed to connect the BESS to the grid. The power electronic cost corresponds to $10EUR/kW$ [5]. In the trading algorithm, the maximum power transfer allowed is 1 MW (times 1.03 for 3% energy losses), resulting in the total power electronics cost of 10 300 Euro/MW. No maintenance cost, land or shielding container for the BESS is taken into consideration.

Battery cost allocation: 45% of the total battery cost is assigned to the 2nd life, as motivated in section 3.1.1.

EoL: EoL is assumed to be at $SoH = 60\%$ as motivated in section 2.2.2.

Cycle weight: The weight of a cycle in the SoH interval 80-70 % is assumed to be 1, whilst the weight for a cycle within the SoH interval of 70-60% is assumed to be 2. This means that a cycle with the same DoD will contribute to a twice as large degradation if $SoH = 70\% - 60\%$ than $SoH = 80\% - 70\%$, in accordance to eq. 2.3. This is a **very rough** estimate based on figure 3.2, which shows the dramatic drop in equivalent full cycles, for some of the cases, after $SoH = 80\%$ [40]. The different weights are assigned as the average slope is flatter between $SoH = 80\% - 70\%$ than $SoH = 70\% - 60\%$.

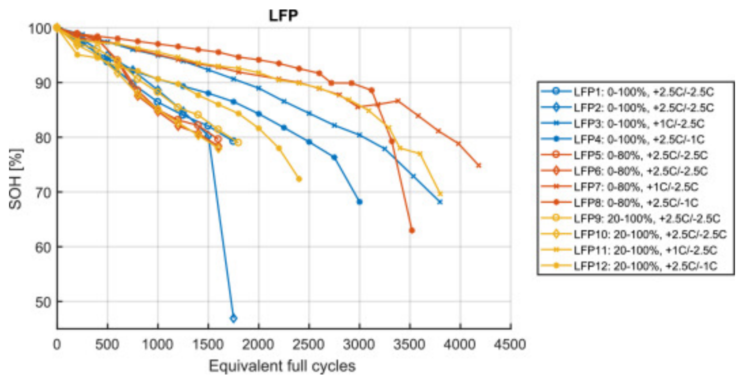


Figure 3.2.: Figure showing number of full cycle equivalents at different SoH's [40].

2nd life battery model

The same logic as described in the 1st life modelling is applied in the 2nd life modelling, with a few additional assumptions mentioned above. The 2nd life modelling is connected to the trading algorithm explained in section 3.1.3. In the 1st life, the SoC-data comes from real drive cycles whilst in the 2nd life, the SoC-data is output data from the trading algorithm.

There are four different initial capacities of the BESS, as the earlier mentioned lifesplit vector is applied in the 1st life modelling. This means that for each trading event, there will be four different data sets as the BESS capacity, costs and earnings differs for the different lifepslit values.

The model is run until EoL, limited by either cycle or calendar life, depending on if the BESS reaches its maximum lifetime in terms of years or SoH first.

3.1.3. Trading algorithm

Applicable assumptions

Historical data: The input values for the market prices (aFRR, FCR-N, FCR-D and day-ahead market) are real data for the period 1/10/2021 - 30/9/2022 [41] [42] [43].

Applicable ancillary services: The services traded are aFRR, FCR-N, FCR-D and buying/selling electricity on the day-ahead market. The reasons why not all services available for trade on the balancing markets are included is due to either technical limitations of the BESS or difficulties in obtaining data for the services.

Costs: Costs, not related to buying energy, are assumed to be limited to grid price tariffs according to Vattenfall's price list for region south 2022 [27]. In Vattenfall's price model, there are some alleviating costs for small electricity producers ($< 1500kW$), which are taken into consideration in the model. Both the costs and reimbursements are based on a connection to the high-voltage grid and the subscription called 'N3' [27], which is described in section 2.3.1.

Markets prices: The capacity market prices are published as an average of the accepted bids or the marginal prices, depending on the service [42] [43]. The trading algorithm always assumes this value, resulting in that the BESS' bids ought to always be accepted as there are usually higher and lower bids in comparison to the average market bid.

Trade statistics: As the bids are always assumed to be accepted, the statistics determines whether the bids are activated or not. The algorithm determines this before entering trade, meaning that the possibilities of generating earnings without being activated is neglected in this model. This is further explained below.

Trade sizes: Trade sizes are limited to SvK's rules, meaning that some of the ancillary services can only be traded in multiples of 0.1 MW, and others in multiples of 1MW.

Thresholds: The trading algorithm operates differently depending on if SoC is outside or within a pre-decided threshold in terms of SoC. This threshold (consisting of $thresh_{high}$ and $thresh_{low}$) is set to be symmetrical around $SoC = 50\%$, to accommodate for both up and down regulations. In the sensitivity analysis (explained in section 3.3) a parameter named *thresh offset* is used, which is either added or subtracted from $SoC = 50\%$ to achieve the desired threshold.

Energy vs. Power trade: It is complicated to decide which ancillary service to trade, as some are traded and reimbursed per energy unit, and others per power unit. This is solved by always comparing the total reimbursement for each service, and assuming that all energy services will provide the grid with X MW during an entire hour, which is the endurance requirement (for energy services) mentioned in section 2.3, making the power and energy trade comparable . This can only be done as the model is treating historical data, knowing all market prices. Real time operation does not have this benefit and is thus less likely to profit from ancillary services than simulated in this report.

Energy losses: Energy losses during (dis)charge are considered to be constant 3% [5].

Input data

The input data for the different services and reimbursement was collected from two different platforms.

The average power capacity reimbursement for FCR-D and FCR-N was collected from SvK's platform 'mimer.svk.se'. On the same platform, the power capacity reimbursement for aFRR could be found, which corresponds to the marginal price [42] [43].

The energy reimbursement data for aFRR and FCR-N was provided by NordPool, who upon contacting them offered to share the relevant data [41]. NordPool also provided the electricity price data for the day-ahead market.

Since the below presented model takes in data in a certain way, the collected data needed to be processed accordingly. During the period for which the data is sampled, the aFRR market changed, moving from a homogeneous Swedish market to differentiating the services for each Swedish electricity price area. This complicated the data collection, and the decision was made that the prices used in the model will always represent the Swedish average, meaning that the study is not performed for a certain electricity price area in Sweden.

Model

The trading algorithm is an essential part of the 2nd life modelling, as it provides the BESS with a set of rules regarding how to trade on the balancing markets, and as an extension of this, how to treat the battery during its 2nd life.

The algorithm is constructed to take in historical data, and given that all data is accessible for each hour, it trades hourly in an optimal way. This means that the algorithm is greedy and that the model only indicates how the trading should have been executed historically, rather than how it actually should trade in real-time. This results in possibly optimistic earnings. However, a greedy algorithm means that it optimizes for each hour instead of taking the entire day into consideration. To exemplify, imagine that at hour **h**, the highest earning potential comes from a down-regulatory service with the value of 200 EUR/MWh. By trading this service, the SoC may be pushed above the upper SoC-threshold, which means that the trading algorithm only allows for services traded for hour **h+1** to be of up-regulatory ones. At hour **h+1**, the same service traded in hour **h** has doubled its value to 400 EUR/MWh, but since we traded a down-regulatory service, pushing us above the threshold, the BESS is not allowed to trade that service. This entails possible decreased earnings, as the algorithm is greedy. Hence, in some ways the algorithm is optimistic due to the use of historical data, and in other ways it is pessimistic due to the greedy nature of the algorithm.

The logic of the algorithm is based upon four base-cases, dependent of the BESS' SoC, current market prices, time during the day and statistics.

At the very start of the trading algorithm, the trading probabilities of a certain hour are taken into consideration. This is done to, in some way, resemble reality and mirror the frequency deviations from 50 Hz. In section 2.3, the statistics for each service is provided, indicating how often a certain service is activated. To accommodate this, the algorithm generates a randomized number for each service which acts as a logical gate that either allows the trade or blocks it based on probabilities. If the trade is allowed, the total reimbursement is calculated, in order to compare the total earnings for each service before deciding which to trade. If the trade is not allowed, the value remains zero. Algorithm 2 displays how this is done.

In algorithm 2, the inbuilt function **rand** is displayed. Rand is used to generate randomized numbers between 0 and 1, with four value digits. Furthermore, the function is uniformly distributed over 0 to 1, excluding the endpoints.

Algorithm 2 Algorithm showing how the probabilities of the different ancillary services, given different grid frequency deviations, are considered in the model. The values in the algorithm are explained in section 2.3.

if $rand < 0.5$ **then**
  $FCRN\_UP_{total} = FCRN(time) + EnergyReimbursement(time)$
  $AFRR\_UP_{total} = AFRR\_UP(time) + EnergyReimbursement(time)$
else
  $FCRN\_DOWN_{total} = FCRN(time) - EnergyReimbursement(time)$
  $AFRR\_DOWN_{total} = AFRR\_DOWN(time) - EnergyReimbursement(time)$
end if
if $rand < 0.01$ **then**
  $FCRD\_UP_{total} = FCRD\_UP(time)$
else if $rand > 0.99$ **then**
  $FCRD\_DOWN_{total} = FCRD\_DOWN(time)$
end if

After completing the probability simulations, four different cases are run through. Case 1-3 are applicable for day-time trading (07.00-22.00), and which case that is applicable depends on the SoC. Case 4 concerns nighttime trading (23.00-06.00), during which the algorithm aims to charge the BESS in the cheapest way possible.

Case 1 treats the scenario when SoC is between $thresh_{low}$ and $thresh_{high}$. The defined threshold-levels are based on Mats Alakülas pre-study, which indicates that the 2nd life cycles should be shallow, with DoD's of $10 - 20\%$, to maximize total energy turnover until EoL [5].

The first rule is to investigate if there are any extreme prices, for the different services, the current hour. An extreme price is defined as a price when a larger trading size (extreme volume = 1MW) is motivated. This is implemented since deeper cycles contribute to larger degradation, which should only be allowed if the potential earnings can be sure to cover the cost of the increased degradation. The extreme price is one of the parameters investigated in the sensitivity analysis.

For extreme prices in Case 1, all services are available for trade, meaning selling electricity, FCR-N, FCR-D up, FCR-D down, aFRR down and aFRR up. However, FCR-D services are prioritized as they do not effect the SoC, entailing negligible degradation. If no FCR-D services are available due to either statistics or price point, the most expensive service, excluding FCR-D, is sold. After the trading event, the SoC (including energy losses for energy services) and earnings are updated accordingly. The algorithm continues the hour-loop, and starts investigating the next hour with a new randomized set of statistics.

If none of the services complies with the probabilities and rules, the algorithm identifies the trade option that generates the largest revenue for the given hour without using extreme price as a trading rule. FCR-D is still prioritized, as long as its earnings corresponds to least 75% of the highest ranked service. This rule was implemented to avoid unnecessary low earnings due to prioritization of negligible degradation. The regular trade is carried out with multiples of 0.1 MW. This entails excluding both aFRR up and down from the non-extreme trade as their minimal bidding volume is 1 MW, as mentioned in section 2.3.2. After the trading event, the SoC (only for energy services, including energy losses of 3%) and earnings are updated accordingly. The algorithm continues the hour-loop and starts investigating the next hour with a new randomized set of statistics.

Case 2 concerns the scenario when SoC is higher than $thresh_{high}$. At those levels, the ambition is to sell energy services in order to reduce the SoC into the pre-defined threshold.

The rules of Case 2 are similar to those of Case 1, with the exception that only up-regulations (FCR-N up and aFRR up) are objects for trading in addition to selling electricity. FCR-D is not included in this list as the goal is to reduce SOC into the threshold. First extreme cases are investigated, followed by regular trade if extremes prices are not available.

After a Case 2 trade event occurs, SoC and earnings are updated and the algorithm continues the hour-loop, and starts investigating the next hour with a new randomized sets of statistics.

Case 3 treats the scenario when SoC is below $thresh_{low}$ and follows the same pattern as the two cases above. In case 3, only down-regulatory services (FCR-N 'down', aFRR down) are objects for trading, in addition to buying electricity. Extreme trade, in case 3, is allowed when the total reimbursement of FCR-N 'down' or aFRR down is greater than zero, as it implies getting paid to charge the BESS.

If there are no extreme cases, the only allowed service to sell is FCR-N 'down', which is prioritized over buying electricity if the total reimbursement for FCR-N 'down' (capacity plus energy reimbursement) is less expensive than the price of buying electricity. If not, electricity is allowed to buy if the current electricity price is lower than the mean electricity price of the day. After a Case 3 trade event occurs, SoC and earnings are updated and the algorithm continues the hour-loop, and starts investigating the next hour with a new randomized set of statistics. If no trade takes place, the algorithm continues to the next hour, blocking trade for that specific hour.

Case 4 treats night trading. The general aim of night trading is to charge the battery, as the data shows that electricity is generally cheaper during the night. The goal is to recharge the BESS up to $SoC = thresh_{high}$, preferably using down-regulatory services if possible. If the SoC is already at, or over, $thresh_{high}$ when night trading starts, no trade will occur until the next morning.

The first rule investigated is if FCR-N 'down' or aFRR down is larger than zero. If that is the case, extreme trade takes place, SoC and earnings are updated, and the algorithm jumps out of the hour-loop, increments, and investigates the conditions for the next hour. However, if no trade takes place, the algorithm investigate the next possibility.

The highest prioritized next move is to sell FCR-N 'down' services if it is cheaper than the current electricity price. If it is, FCR-N is traded, SoC and earnings are updated and the loop continues. If no trade occurs, the next step is to investigate if the electricity price is lower than the mean electricity price of the day. If yes, electricity is traded with the size of $\frac{1}{8} \cdot NightVolume$, where $NightVolume$ corresponds to the total amount of energy that needs to be charged during the night to reach $thresh_{high}$, and $\frac{1}{8}$ correspond to the eight hours during which night trading occurs.

After an entire day of trading has proceeded, the rainflow algorithm treats the SoC data of the day, calculates the total degradation and subtracts it from the current SoH. Additionally, after the day has ended, the accumulated earnings are adjusted with the degradation cost and grid connection costs/reimbursements.

3.2. Test cases and sensitivity analysis

To answer the sub questions in section 1.2, the developed model needs to be tested on different scenarios, followed by a sensitivity analysis.

In order to investigate if different 1st lives effect what the optimal cycling should look like in the 2nd life, two vehicles are studied; truck A and truck B.

Truck A has a different driving and charging profile. It operates five days per week and stands still during the weekends. A normal day roughly consists of one cycle with $DoD = 60\%$ and another with $DoD = 75\%$ with intermediate charging to $SoC = 100\%$, during a period of approximately eight hours, followed by night charging.

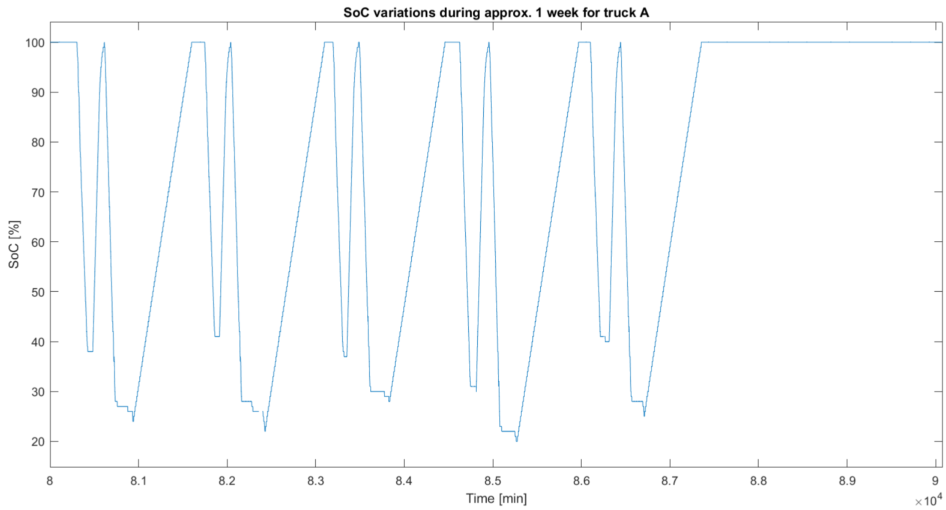


Figure 3.3.: Figure showing snapshot of SoC variations for truck A of approx. one week of operations.

Truck B is in operations seven days a week, 24 hours a day, with occasional one or two days of standing still. The cycles in general are between $DoD = 40\%$ *to* 70%, and one day fits approximately five cycles, with intermediate charging.

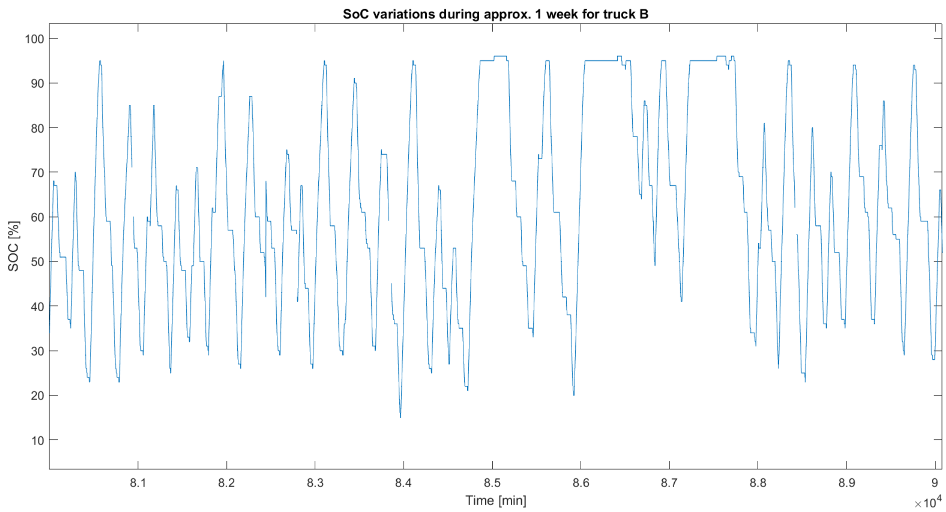


Figure 3.4.: Figure showing snapshot of SoC variations for truck B of approx. one week of operations.

3.3. Sensitivity analysis

The sensitivity analysis is performed through a parameter sweep of the entire model. The chosen parameters, and corresponding values, for the analysis are presented in table 3.1.

Table 3.1.: Parameters and values which are objects for sensitivity analysis.

Parameter	Values	Unit
Calendar life	**10**, 20	[years]
NoC factor*	1, **2**, 6	-
Thresholds**	**40%-60%**, 30%-70%	-
Extreme price	100, **250**, 400, 550, 700, 850, 1000	[EUR/MW]
Trade size	0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, **0.9**, 1	[MW/trade event]
LifeSplit	0.2, 0.3, **0.6**, 0.9	-

1.* NoC factor represents the factor which the NoC-vector should be multiplied by to investigate the effect of different C-rates and other battery cycle life expectations.

2.** Thresholds are generated by using different 'thresh offsets', that either take on the value 10% or 20%, resulting in thresholds of either 50% ± 10% or 50% ± 20%.

3. The bold values in table 3.1 make up a base case which will be used in chapter 4.

These parameters form a nestled for-loop, which allows all combinations of the different parameters. Outside the two innermost for-loops mesh matrices are initiated. Then, for every combination of extreme price vector and trade size vector, the 1st and 2nd life model is run, resulting in calculations of total earnings, expected life time and number of trades; with which the mesh matrices are populated. When all combinations of extreme price and trade size have been traversed, the matrices are used to plot a surface. This is repeated for every setting of the three other vectors, i.e. calendar life, NoC factor and thresh offset. This is shown in algorithm 3.

Algorithm 3 Algorithm showcasing the sensitivity analysis in the form of nestled for-loops.

```
Calendar life vector = [10, 20]
NoC factor vector = [1, 2, 6]
Thresh offset vector = [10, 20]
Extreme price vector = [100 : 150 : 1000]
Trade size vector = [0.1 : 0.1 : 1]
for Calendar life in Calendar life vector do
    for NoC factor in NoC factor vector do
        for Thresh offset in Thresh offset vector do

            Initiate mesh matrices

            for Extreme price in Extreme price vector do
                for Trade size in Trade size vector do

                    Run 1st and 2nd life model

                    Populate mesh matrices with results from above run

                end for
            end for

            Plot mesh matrices

        end for
    end for
end for
```

Lastly, a standalone sensitivity analysis is performed, which investigates how the earnings are effected, if the market prices would drop by 50%. This price drop could potentially simulate another market or a possible Swedish/Nordic market saturation.

Chapter 4.

Results and analysis

The below presented results are a few chosen graphs for different parameter combinations followed by an analysis. Not all results will be discussed as all combinations from the sensitivity analysis are too many. However, in Appendix B, all results will be presented in the form of figures, but not further discussed.

Almost all figures in the below chapter display four different results simultaneously in the form of four different colours. These colours represent the lifesplit vector, ergo different shares of the life spent in the 1st respectively 2nd life.

4.1. Payback, cycle counting and trading

The results presented in figure 4.1, 4.2 and 4.3 represent the base case mentioned in table 3.1 and showcase when truck A is in operations during the 1st life and the 2nd life parameters are NoC factor of 2, calendar life of 10 years, threshold of between 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros. Figures 4.1 and 4.3 both include the four different lifesplit cases, denoted by the different colours in the diagrams. Figure 4.2 only displays the rainflow matrix for the battery with the relative lifesplit of 0.6.

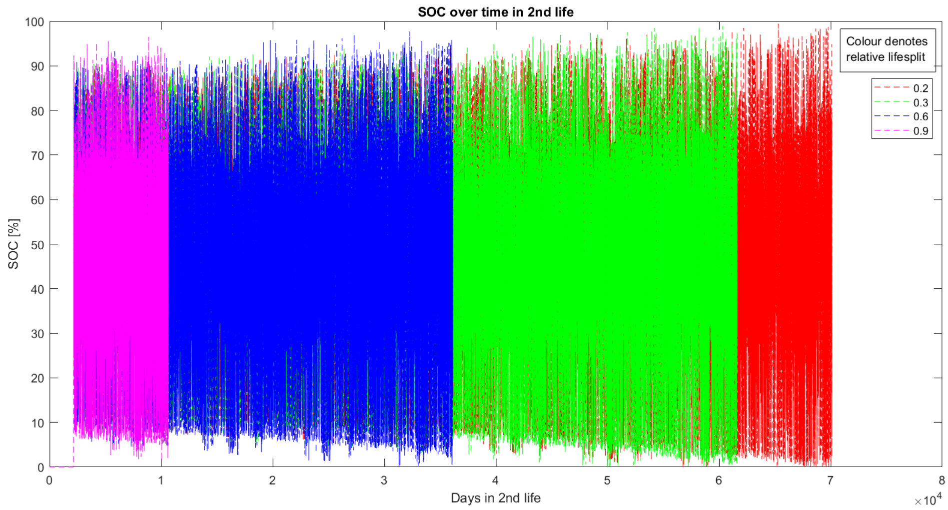


Figure 4.1.: Figure displaying how SoC varies during the 2nd life until EoL for truck A, with the chosen parameters of NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

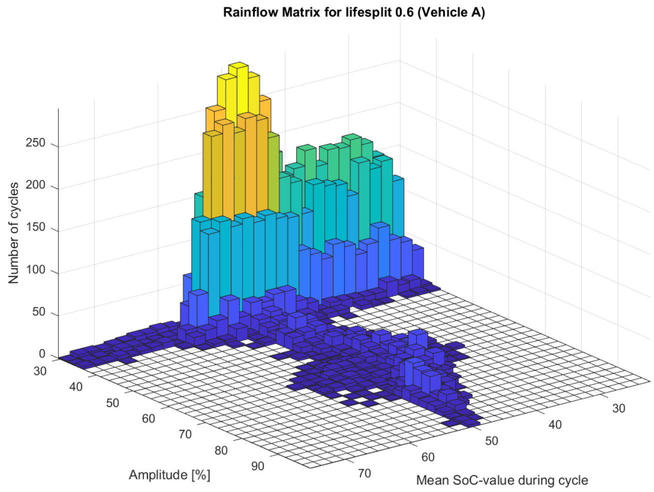


Figure 4.2.: Rainflow matrix for truck A with the chosen parameters of lifesplit vector of 0.6, NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

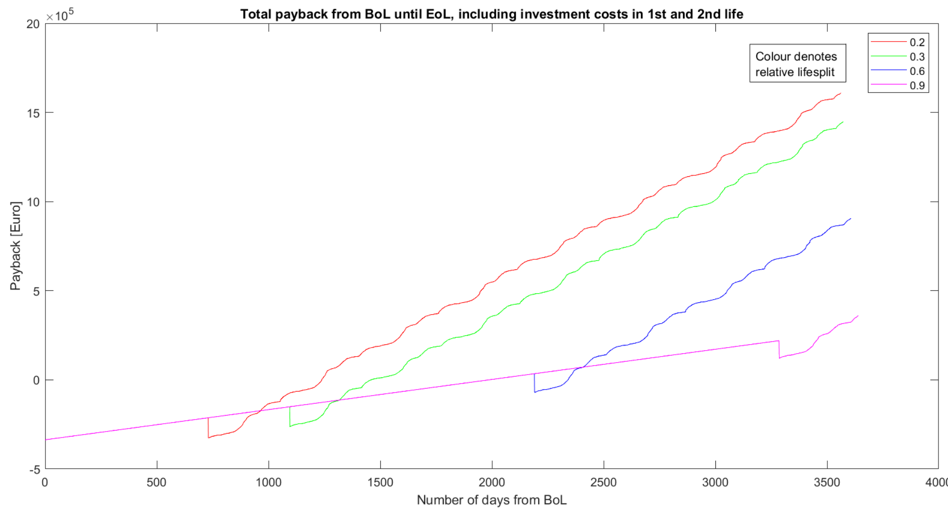


Figure 4.3.: Total payback from BoL until EoL for truck A, including investment costs, for the case of NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

The same parameters and results are shown in figures 4.4, 4.5 and 4.6, with the difference that Vehicle B is in operations during the 1st life.

Vehicle B, as mentioned, is subject for a rougher treatment than vehicle A during the 1st life. This means that it will spend less total time in terms of days in the 1st life. As a result of this, the total payback is higher for all lifesplit cases for Vehicle B than Vehicle A. This means that a harder treatment in the 1st life contributes to higher total earnings, as the treatment eventually will force the battery out of the vehicle sooner, and therefore generate higher total earnings per calendar day as seen in figure 4.3 and 4.6.

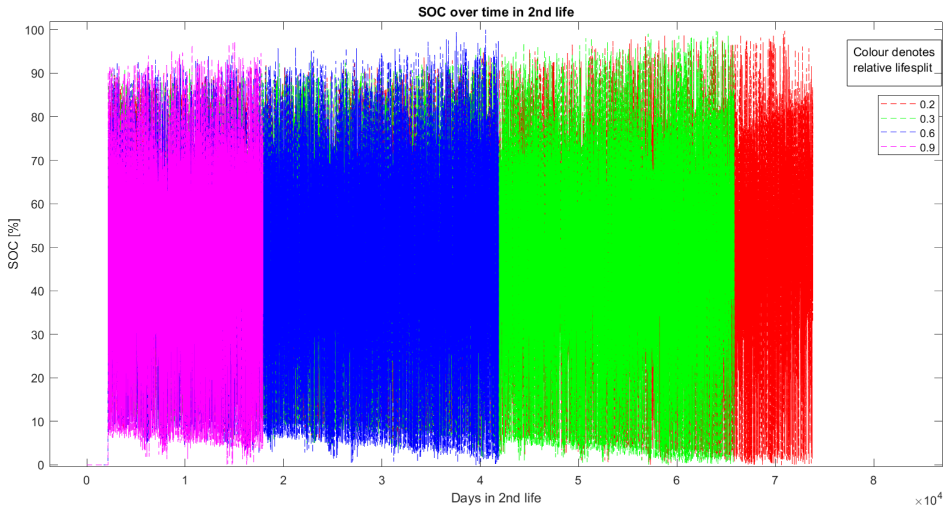


Figure 4.4.: Figure displaying how SOC varies during the 2nd life until EoL for truck B, with the chosen parameters of NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

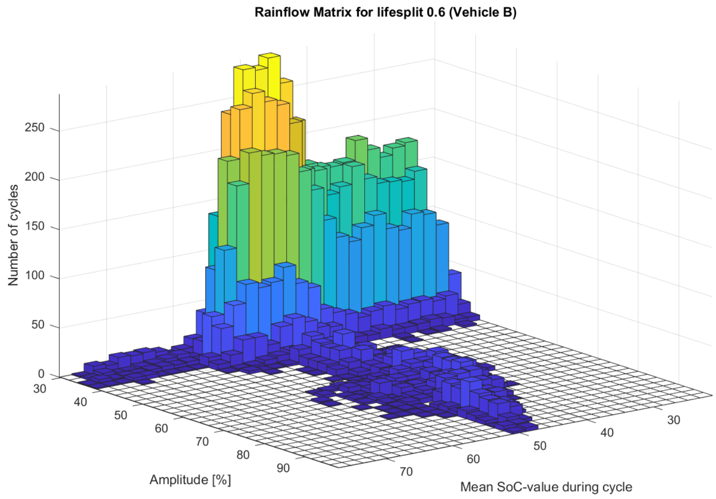


Figure 4.5.: Rainflow matrix for truck B with the chosen parameters of lifesplit vector of 0.6, NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

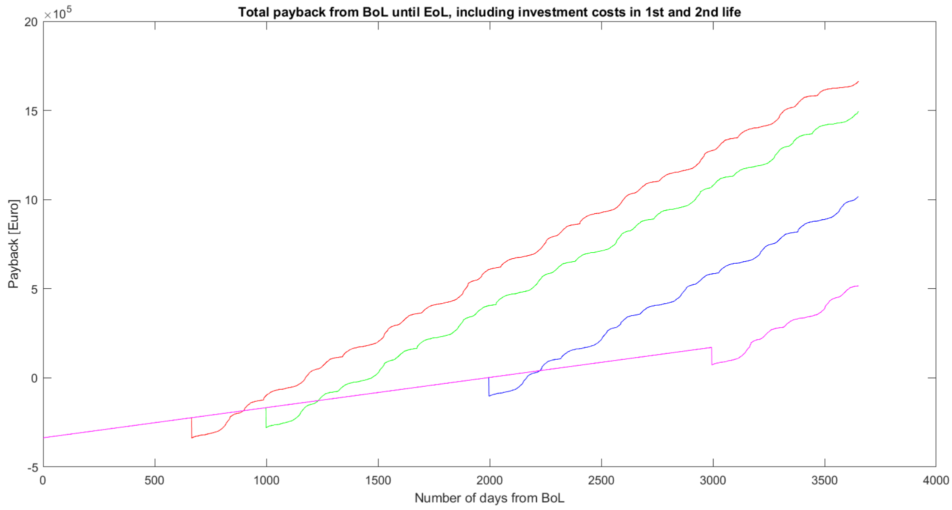


Figure 4.6.: Total payback from BoL until EoL for truck B, including investment costs, for the case of NoC factor of 2, calendar life of 10 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

Analysis

The most important result from figure 4.1 is that the the trade most often occurs in the span of 70-20%, which can be seen in 4.1 and 4.4 as there is almost a solid band between those levels, in comparison to higher and lower SoC's where the trade density is lower.

Another important result from figure 4.1 is that the SoC limits are diverging over time, closing in on the extremas of 0 and 100%. This stems from the degrading battery and decreasing battery capacity, making an 'energy trade size' of e.g. 0.8 MWh larger in terms of DoD's. This phenomena is most visible when observing SoC's of 10% and under, where a line with a negative slope could be fitted.

The same trend is not as prominent for higher SoC's, which most probably is due to the trade bias of the BESS. The BESS prioritizes, due to the implemented trading rules, selling energy in form of electricity or up-regulatory services instead of down-regulatory services, as the possible revenues for up-regulatory services naturally exceed down-regulatory services. This means that the probability of reaching low SoC's, as energy is sold, is higher than reaching high SoC's, which is why the negative slope is visible for low SoC's. This is supported by figure 4.2 and 4.5, which shows more identified cycles around low means in comparison to high means, meaning that more trade events occur at lower SoC's than higher SoC's.

The trading patterns presented in figure 4.1 and 4.2 result in the total payback showed in figure 4.3.

Regarding the payback, the most evident result is that the total payback is highest for the batteries which are removed from the vehicle the earliest, i.e. the batteries which has the lowest lifesplit vector value. This result is motivated by the fact that an energy cycle is worth more in the 2nd life than the 1st life.

In figure 4.3 all batteries operate the same number of days. This result is expected as all the BESS' are limited by calendar aging instead of cycle aging. When running the same parameters again, but with the calendar life of 20 years, the payback looks as figure 4.7, where the expected lifetime differs for the four different BESS'.

Figure 4.7 also shows that the degradation in 1st is smaller than 2nd life, as the batteries that spend the least time in the 1st life reach EoL earlier than the batteries that spend more time inside the vehicle.

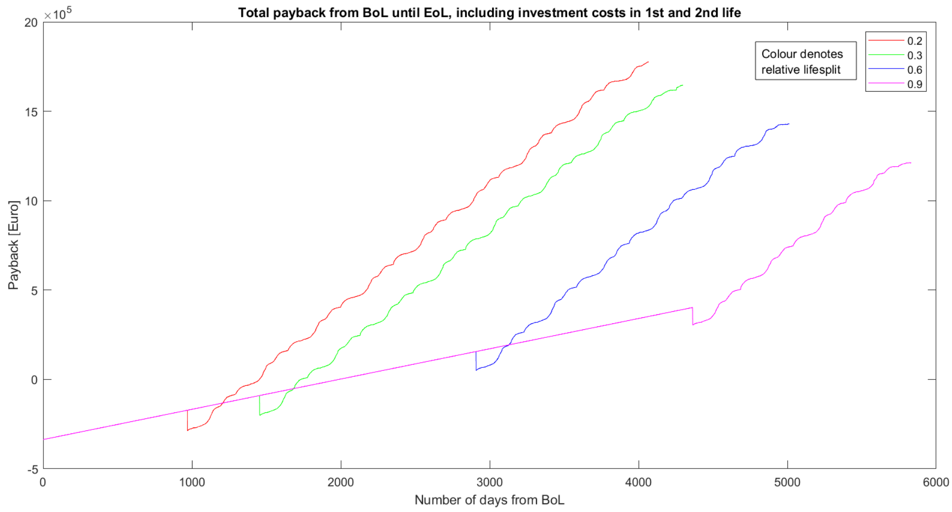


Figure 4.7.: Total payback from BoL until EoL, including investment costs, for the case of NoC factor of 2, calendar life of 20 years, threshold of 40-60%, trade size of 0.9 MW/trade event and extreme price of 250 euros.

4.2. Sensitivity analysis

4.2.1. Different NoC-factors

The different NoC-factors relate to figure 1.1 and when $NoC\ factor > 1$, the lines in figure are shifted up along the y-axis. A higher NoC-factor can either entail a lower C-rate, meaning that you treat the battery kinder, or a higher belief in the battery's expected cycling life, claiming that it can endure more cycles than the blue line in figure 1.1 suggests.

The NoC-factors that are investigated are 1, 2 and 6. NoC-factor 1 is an approximation of the blue line in figure 1.1, NoC-factor 2 is an approximation of the red line in figure 1.1 (0.5 C) and lastly, NoC-factor 6 is an approximation of a battery that is believed to endure 3 times as many cycles as the battery in figure 1.1, being (dis)charged with 0.5 C. The below presented results in figures 4.8, 4.9 and 4.10 concerns a 1st life driven by truck A, batteries with a calendar life of 20 years and a defined threshold of 30-70%.

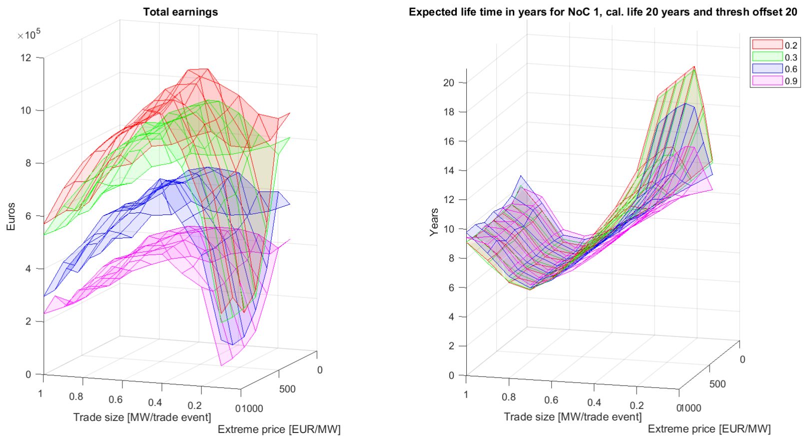


Figure 4.8.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%.

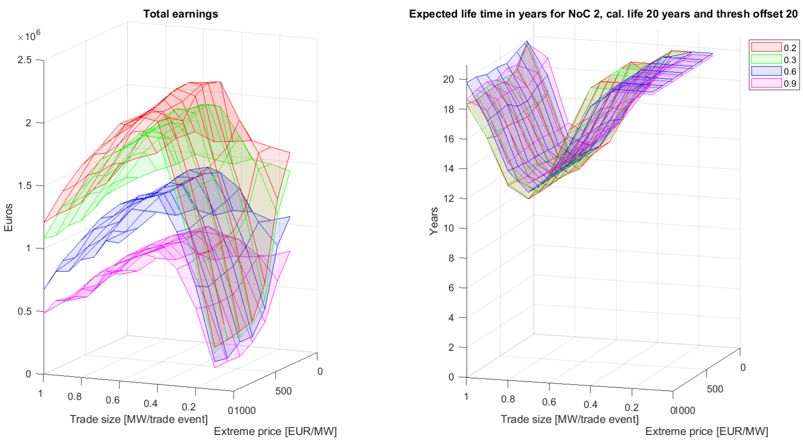


Figure 4.9.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%.

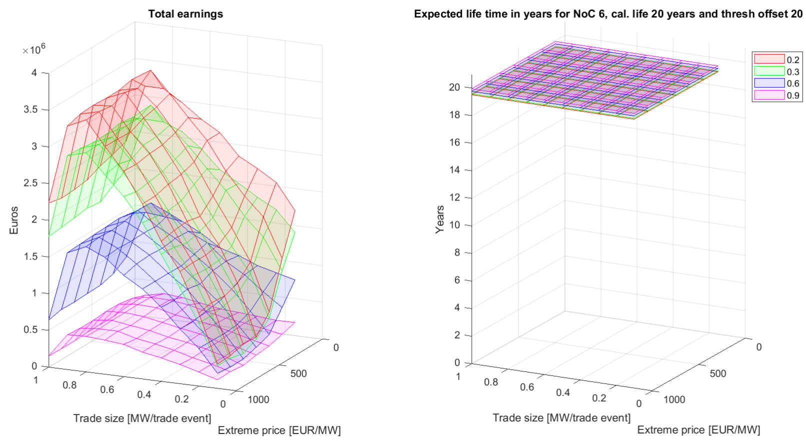


Figure 4.10.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%.

Analysis

Figures 4.8 and 4.9 share similar appearance, as they have prominent max values of total earnings (left plot) along a certain value of trade size (max at trade size = 400 [MW/trade event]), entailing that the extreme price is not as an important factor regarding the earnings for NoC's of either 1 or 2. Additionally, if the expected life time is observed in the same figures, it is clear that they both have minimum values for a certain trade size, which is seemingly indifferent along the extreme price axis.

The appearance mentioned above is not found in 4.10. There is still a clear maximum value along a trade size (max value at 0.8 [MW/trade event]), but the trade size is significantly larger than for those of figure 4.8 and 4.9. When analyzing this, in combination with the expected life time, one conclusion is rather obvious. For the case of NoC-factor 6, the degradation for a cycle is either worth a $\frac{1}{6}$ or a $\frac{1}{3}$ of the cycles in the case of NoC-factor 1 respectively 2. The low degradation for NoC-factor 6 entails that the BESS will, in all cases presented in figure 4.10, be limited by the calendar life rather than the cycling life. For that reason, the optimal trade size is larger in figure 4.10 than in figures 4.8 and 4.9, in order to maximize the total energy turnover until EoL, which is not limited by the calendar life. The conclusion of this is that for very low C-rates or good battery characteristics, it is economically beneficial to cycle the BESS deeper.

In addition to this, the same analysis can be done for the extreme price in the different figures. For figure 4.8 and 4.9, the extreme price which generates the highest earnings is 400 EUR/MW, whilst in figure 4.10 the optimal extreme price is 250 EUR/MW. A lower extreme price means a higher frequency of extreme trades, as the algorithm allows more extreme cases to pass through its logical gate, which in turn entails a larger degradation which coheres with the reasoning in the section above. This can further be confirmed by observing figures 4.11, 4.12 and 4.13, which show the normalized value of the number of total trade events respectively extreme trade events, for the three cases above. The normalization was carried out by dividing the number of trade events with the expected life time in the 2nd life, to avoid any bias in the analysis, as naturally more trade events will occur if the BESS spends more time actively trading in the 2nd life. The figures clearly show that for the maximum earning values (marked in the figures), the number of extreme trades are almost the double for NoC-factor 6 in comparison to NoC-factor 1 and 2.

Furthermore, figures 4.8 and 4.9 show interesting valleys in the expected life time results (trade size equal to 0.7 MW/trade event for both figures). The reason behind this appearance is of course the trading algorithm, which allows significantly more trading events for a trade size of 0.7 than e.g. 0.8 [MW/trade size]. To clarify this, figures 4.11 and 4.12 both have a 'knee' at 0.7 [MW/trade event], showing that the number of trade events drastically decreases for trade sizes larger than 0.7 [MW/trade event]. This means that in the case of a trade size of 0.7 [MW/trade event], many trade events are approved by the algorithms logical gates, whilst larger trade sizes are blocked. This is most probably due to the nature of the battery which is modelled, meaning that a trade that will result in a $SoC > 100$ or $SoC < 0$ will be blocked. The extension of this is that trade size of 0.7 [MW/trade event] will be allowed almost as many times as smaller trade sizes. Since they are traded almost as many times, the trade size of 0.7 [MW/trade event] will have the largest accumulated degradation, resulting in the expected lifetime valley.

Lastly, the slope on both sides of the earnings maxima can also be explained by the reasoning above. For figures 4.8 and 4.9, the slope is steeper towards smaller trade sizes from the maxima, and flatter towards larger trade sizes from the maxima. This is linked to the trade-off between number of trades and degradation. For larger trade sizes, the number of trades decreases drastically but the earnings for each performed trade event increases. Also, the degradation cost decreases as the number of trade decreases significantly. This means that the dominating factor for the total earnings are the increased revenues from trade and not the degradation due to the large share of blocked trades. For smaller trade sizes, the increased number of trades is not as significant as for the above mentioned case, resulting in a steeper slope as the total earnings decrease drastically.

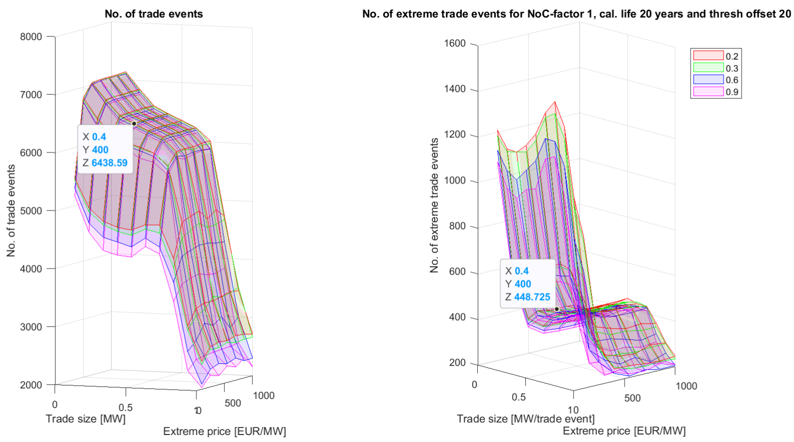


Figure 4.11.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%. The marked points represent the combination which generates the highest total earnings.

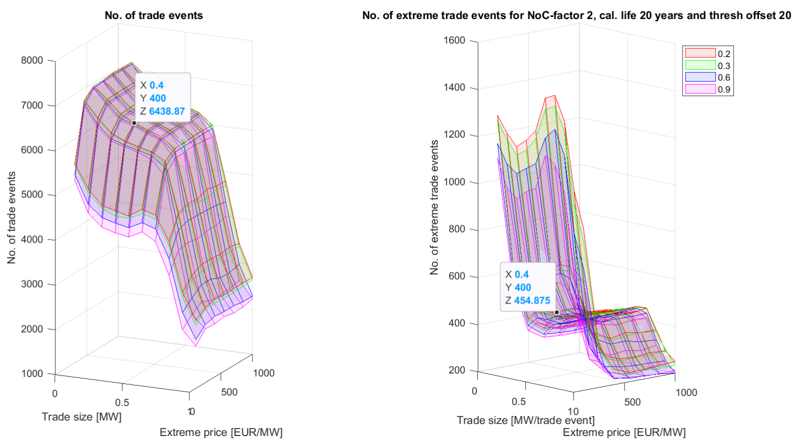


Figure 4.12.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%. The marked points represent the combination which generates the highest total earnings.

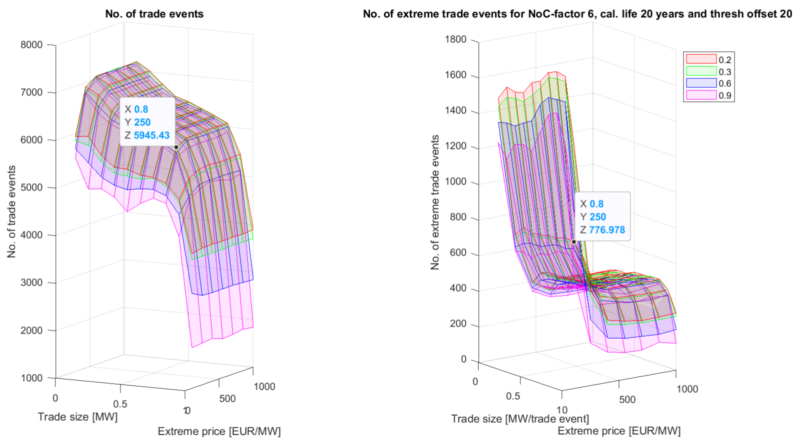
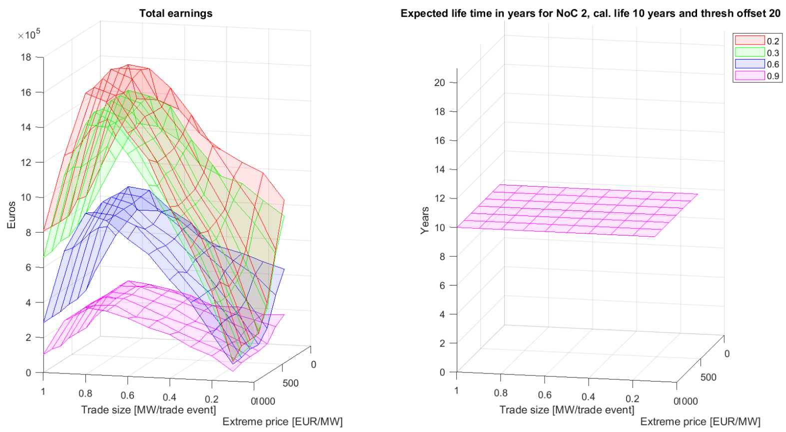


Figure 4.13.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%. The marked points represent the combination which generates the highest total earnings.

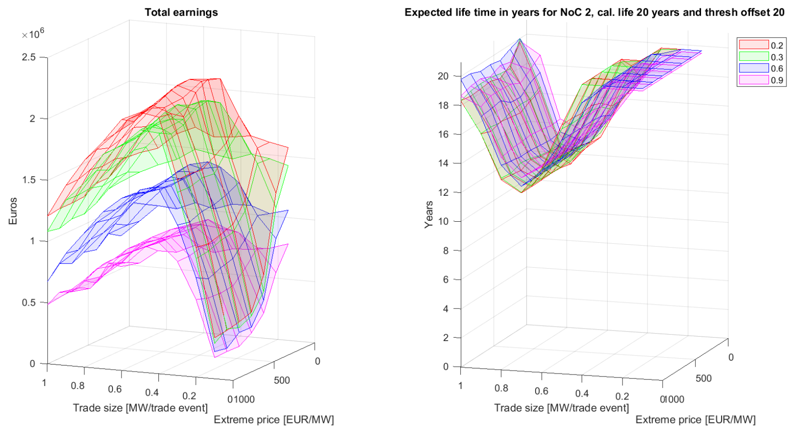
4.2.2. Different calendar life

The investigated calendar lives are 10 and 20 years.

The below presented results in figure 4.14a represents a 1st life inside truck A, a NoC-factor of 2, a calendar life of 10 and a threshold interval defined as 30-70%. The corresponding result for a calendar life of 20 years can be found in figure 4.9, which is also repeated in figure 4.14b, for a facilitated comparison.



(a)



(b)

Figure 4.14.: Figures displaying total earnings and expected life time with a NoC factor of 2 and threshold between 30-70%.Figure 4.14a has a calendar life of 10 years, whilst figure 4.14b has a calendar life of 20 years. For figure 4.14a, all four lifesplit simulations reach expected life time of ten years, resulting in only the pink surface showing.

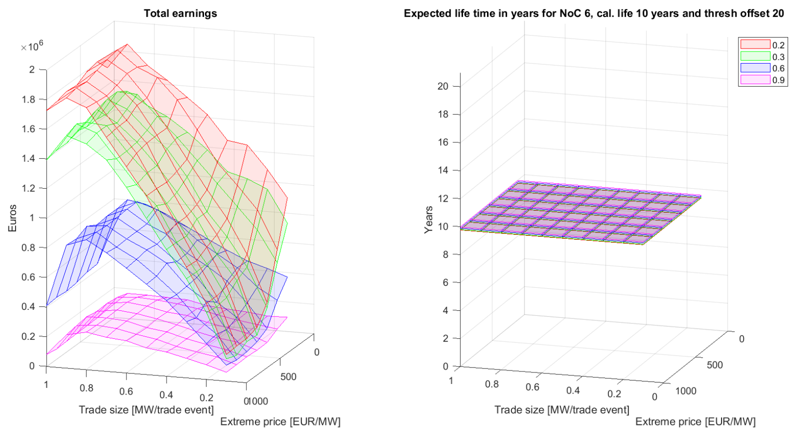
Analysis

The most prominent difference of figures 4.14a and 4.14b (figure 4.9) is the maximum total earnings, which is naturally higher in figure 4.14b as the calendar life is higher, allowing for more total trade events.

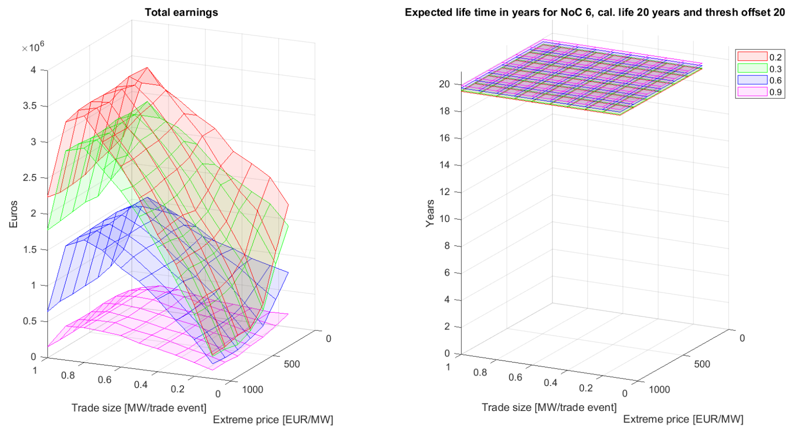
For figure 4.14a, the optimal trade size is larger than for figure 4.14b. This, as many other phenomenons, can be explained by the limiting calendar life, meaning that if the calendar life is the limiting factor, the batteries should be cycled harder in order to get a larger energy turnover as the degradation is less significant as the life is limited by the calendar aging.

Additionally, if the two different calendar results are compared for NoC-factor 6, the maximal earnings are almost doubled, see figures 4.15a and 4.10 (repeated in figure 4.15b for facilitated comparison). This can be explained as the two cases are both limited by the calendar life, meaning that they are optimally cycled in the same way, where a larger trade size is prioritized.

This stands in contrast to figure 4.14a and 4.14b, where the total earnings are larger for figure 4.9, but not as significant as the case with NoC factor 6. By observing figure 4.14b, it is evident that the case of maximal earnings do not use the entire available 20 years to trade, but rather somewhere around 14-17 years, which is the reason why the total earnings do not double when the calendar life doubles. Figure 4.14a is limited by the calendar life, which results in an increased optimal trade size. On the other hand, in figure 4.14b, very few cases (and only cases with small trade sizes) are limited by the calendar life, meaning that the majority of the cases are being limited by the cycling life. This causes the optimal trade size to shift towards smaller sizes in order to balance earnings per trade, battery degradation and algorithm trade blockage.



(a)



(b)

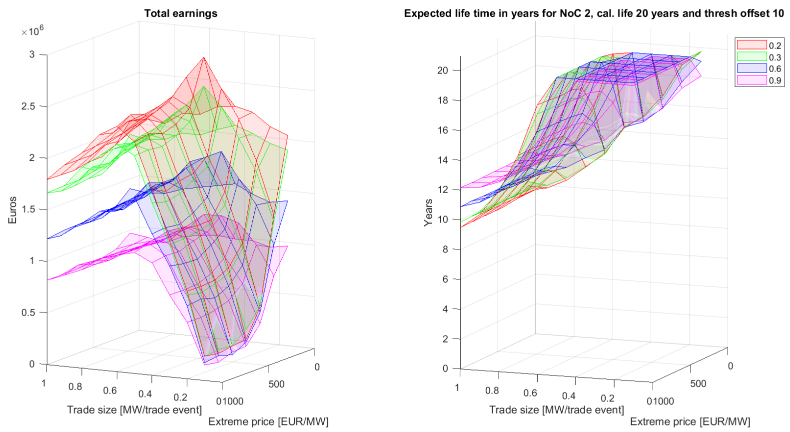
Figure 4.15.: Figures displaying total earnings and expected life time with a NoC-factor of 6 and threshold between 30-70%. Figure 4.15a has a calendar life of 10 years, whilst figure 4.15b has a calendar life of 20 years.

4.2.3. Different thresholds

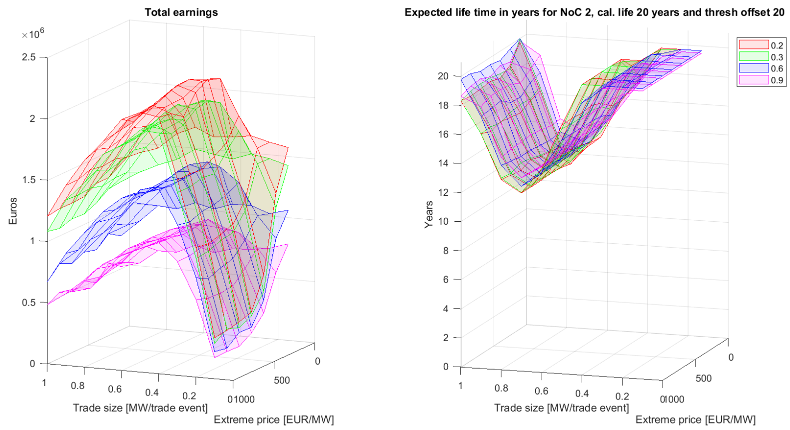
The two different thresh offsets that are investigated are 10 and 20, representing thresholds of 40-60% respectively 30-70%.

The below result in figure 4.16a represent a battery which spent its 1st life in truck A, a thresh offset of 10 (i.e. threshold 40%-60%), with a NoC-factor of 2 and a calendar life of 20 years.

Figure 4.9 represent the same parameters as above, but with the thresh offset of 20. A copy of figure 4.9 can be found below figure 4.16a (in figure 4.16b), to facilitate comparison.



(a)



(b)

Figure 4.16.: Figures displaying total earnings and expected life time with a NoC factor of 2 and calendar life of 20 years. Figure 4.16a has a threshold between 40-60%, whilst figure 4.16b has a threshold between 30-70%.

Analysis

The total maximal earnings are higher for threshold 40-60% than 30-70%, as shown in figures 4.16a and 4.14b. This can be explained by observing figures 4.12 (threshold 30-70%) and 4.17 (threshold 40-60%), which show that the number of extreme trades are almost the double for the combination resulting in the highest total earnings, for the case with the threshold 40-60%.

A smaller threshold leads to more extreme trade events as there is a greater possibility that an extreme trade will be allowed due to the trading rules. One of the trading rules, explained in chapter 3, is that a trade can occur when the initial SoC is inside the threshold $thresh_{low} < SoC_{initial} < thresh_{high}$, meaning that extreme trades can occur as long as the SoC after the trade has taken place (SoC_{after}), holds for $0 < SoC_{after} < 100$. If the threshold is between 30-70%, more extreme trades will be blocked due to this simple rule, meaning less extreme trades, resulting in a lower total maximal profit.

However, figure 4.1 and 4.4 show that the BESS more frequently trade up-regulatory services or sell electricity, meaning that the larger threshold could be more beneficial if it was shifted upwards to e.g. 40-80%. This has not been tested in the model and therefore no results of this is presented.

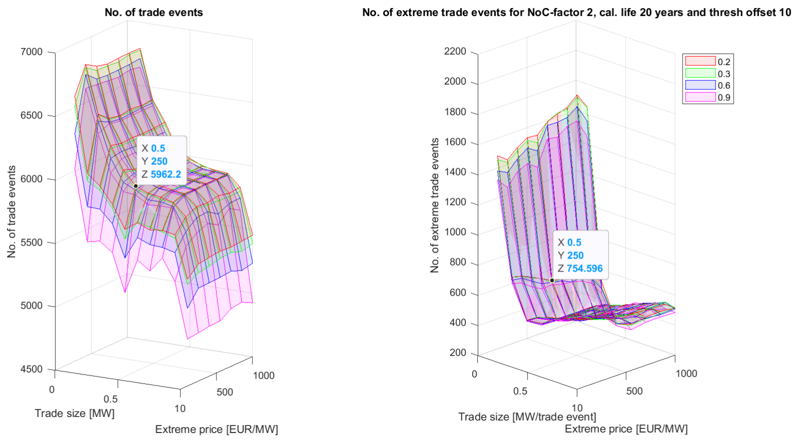


Figure 4.17.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 40-60%. The marked points represent the combination which generates the highest total earnings.

4.2.4. Highest and lowest total earnings

The highest and lowest total earnings for batteries in vehicle A during the 1st life are presented in figure 4.18 and 4.19.

The lowest total earnings until EoL (the best earnings of the lowest overall case) is achieved with a BESS with the least favourable characteristics, i.e. NoC factor of 1, calendar life of 10 and threshold between 30-70%. The total earnings reaches a maximal value of approximately 1.1 million euros until EoL for a battery that spends only 20% of the available capacity reduction in the 1st life (red surface in figure 4.18).

The highest total earnings until EoL is achieved with a BESS with the most favourable characteristics, i.e. NoC factor of 6, calendar life of 20 and threshold between 40-60%. The total earnings reaches a maximal value of approximately 4.55 million euros until EoL for a battery that spends only 20% of the available capacity reduction in the 1st life (red surface in figure 4.19).

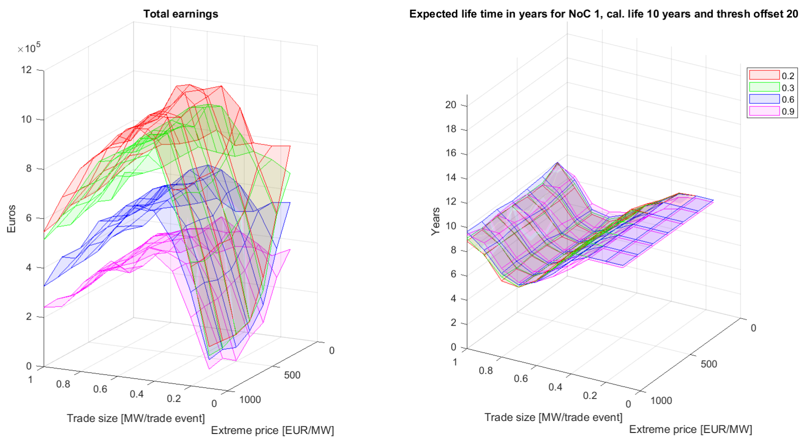


Figure 4.18.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%. This result represents the overall lowest total earnings for all simulations.

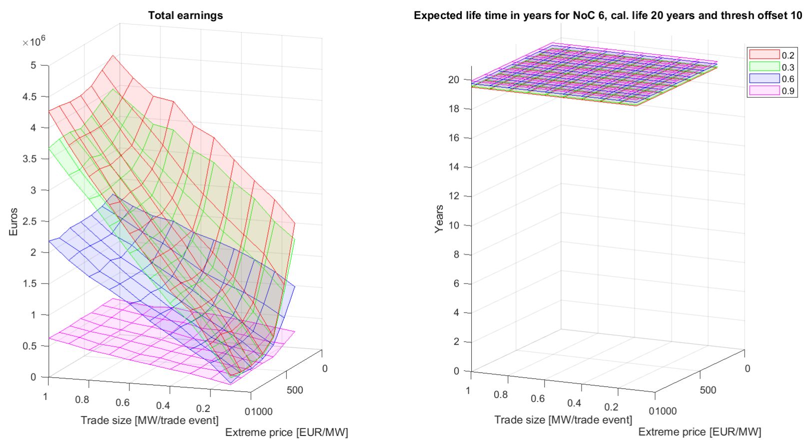


Figure 4.19.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%. This result represents the overall highest total earnings for all simulation.

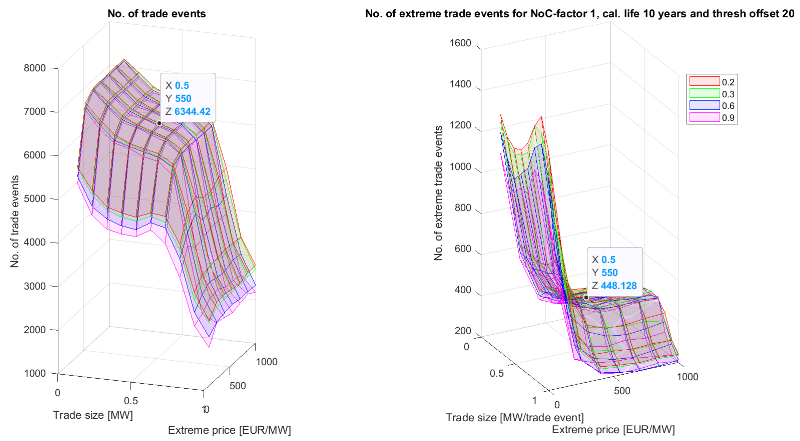


Figure 4.20.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%. The marked points represent the combination which generates the highest total earnings.

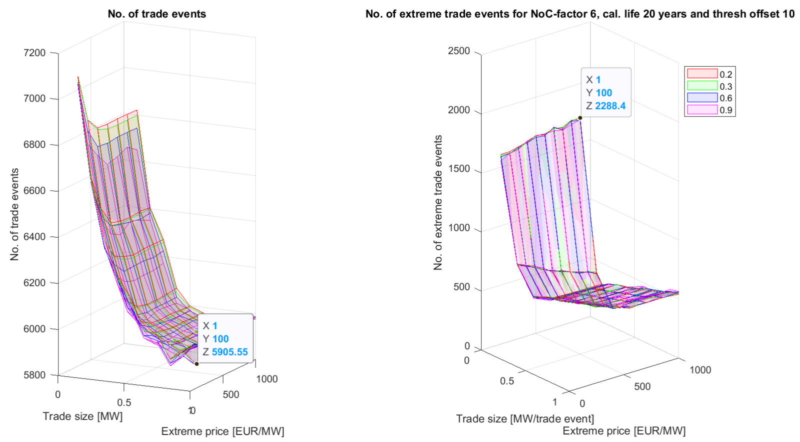


Figure 4.21.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%. The marked points represent the combination which generates the highest total earnings.

4.2.5. Lower market prices

The results presented in figure 4.22 and 4.23 represent the same simulation as figures 4.18 and 4.19, with the exception that the market prices for electricity, aFRR, FCR-N, FCR-D and energy reimbursement are halved.

The displayed results are the ones that generated the highest and lowest overall earnings. The highest total earnings sum up to approximately 1.5 million euros, respectively 270

000 euros for the lowest total earnings, for the lifesplit case of 0.2 (red surface in both figure 4.22 and 4.23).

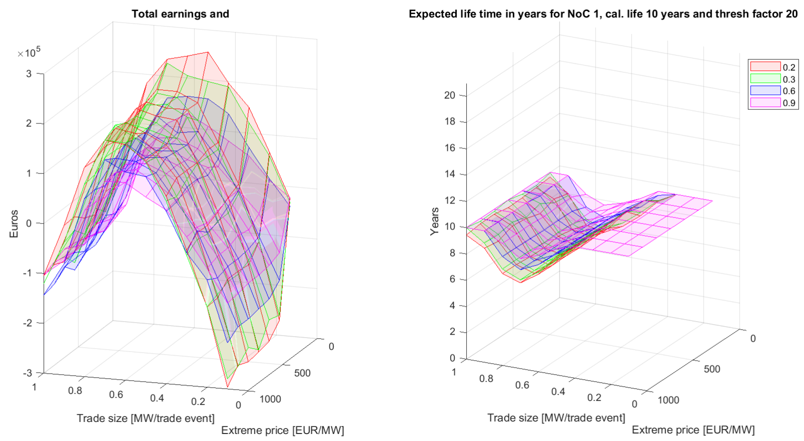


Figure 4.22.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%. This result is simulated by using halved market prices for all trading events.

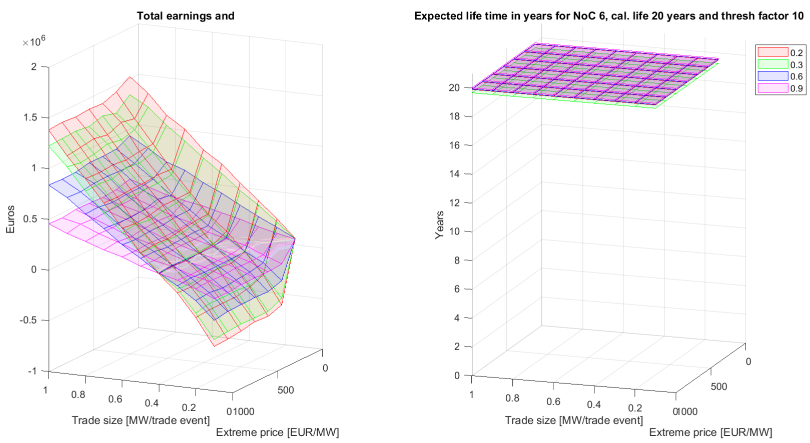


Figure 4.23.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%. This result is simulated by using halved market prices for all trading events.

Analysis

In the results presented above, the market prices were halved, which resulted in decreased total earnings by a factor of four. The reason why the earnings decreased by a factor twice as large as the market price decrease is largely due to the extreme trade's earnings potential in the optimal combination of trade size and extreme price. When comparing figures 4.25 and 4.24 with 4.21 and 4.20, the normalized extreme earning potentials for the halved market prices cases are approximately 120 000 euros (1181 · 100 [euros]) respectively 86 500 euros (865 · 100 [euros]). For the 'regular' market prices the normalized extreme earning potentials are approx. 229 000 euros (2288 · 100 [euros]) respectively 246 000 euros (448 · 550 [euros]). Keep in mind that these numbers are normalized and thus are to be multiplied with the number of years in 2nd life, to actually show how many trade events that occurred until EoL. This largely contributes to lower earnings. However, the reason why the algorithm optimizes in the marked points, particularly in the 'lowest earnings' case, is yet inconclusive and needs to be further investigated.

Furthermore, some combinations of trade size and extreme price generate 'negative earnings' in the case of a 50% market drop, which can be seen in figure 4.22 and 4.23. The reason behind this is probably the costs, presented in table 2.1, related buying and selling energy and power, meaning that the potential revenue is too low to cover all the costs.

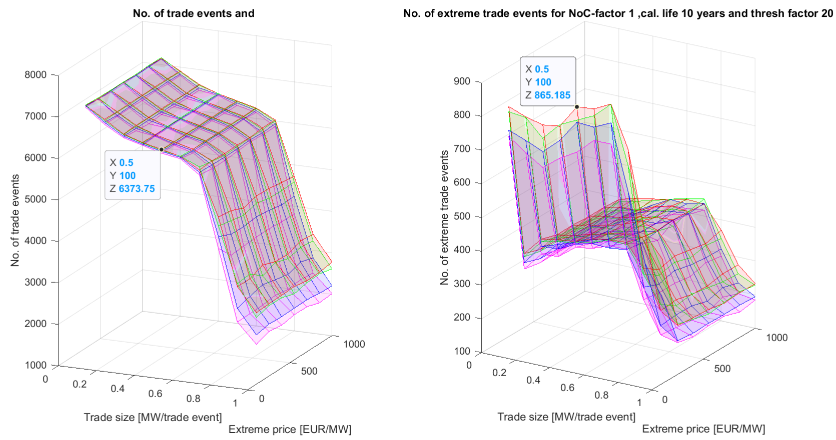


Figure 4.24.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%. The marked points represent the combination which generates the highest total earnings. This result is simulated by using halved market prices for all trading events.

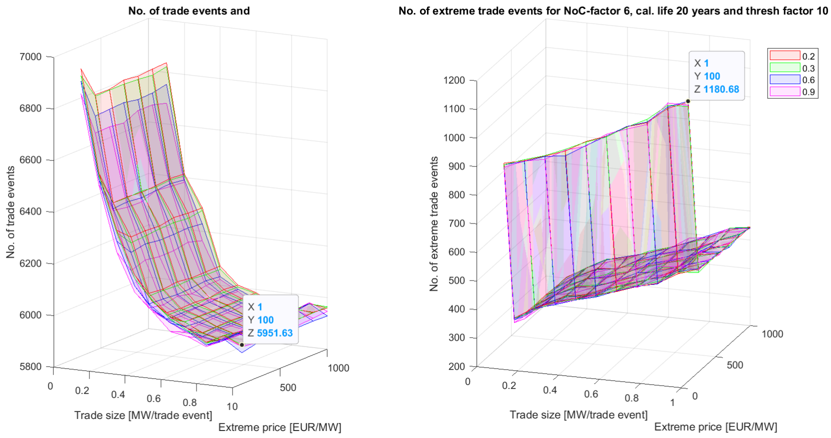


Figure 4.25.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%. The marked points represent the combination which generates the highest total earnings. This result is simulated by using halved market prices for all trading events.

Chapter 5.

Discussion

In chapter 4, the results are presented by observing how one parameter change the total earnings. In this chapter, the overall trends and optimal combinations will be discussed, as well as implications of the results and a discussion of how cautiously the results should be viewed.

5.1. General trends

In general, the results are promising and show that BESS investments will, in all investigated cases, generate a positive total payback. The most evident trend is that the total earnings are maximized the sooner the batteries are taken out of the vehicles. This extends to the preference of cycling the battery deeper during the 1st life, in order to take out the batteries earlier in terms of days, if the calendar life is the limiting factor.

With this in mind, one conclusion is that commercial vehicle (CV) batteries are more suitable for 2nd life applications, than personal vehicle batteries, as the CV batteries are cycled rougher, meaning that they naturally spend less time in the 1st life than the personal vehicle batteries. Many personal vehicles are driven carefully and used for daily commutes which do not contribute to deep DoD's. The extension of this is that the personal vehicle batteries eventually will be limited by the calendar life rather than the cycling life, maybe even before the SoH has reached 80%.

Furthermore, the largest revenues are generated for the batteries with the best characteristics, which is largely due to the fact that the batteries can be cycled deeper, without being limited by neither the cycling nor calendar life. Deeper cycles lead to larger earnings as more power/energy is sold. In contrast, the smallest revenues are generated by the cases with the worst battery characteristics.

An important insight of the results is how to treat the batteries in order to maximize the revenue. The conclusion is that the ideal treatment is highly dependent of the battery characteristics and the algorithm trading rules. For high performing batteries, the treatment should be rougher, and the opposite is valid for less high performing batteries. In addition to this, the trading rules of the algorithm must be considered, and the 'number-of-trading knee', where few trade events are blocked, needs to be identified, as discussed above in chapter 4.

Regarding the sensitivity analysis, it is evident that the NoC-factor effects the total earnings the most, as it 'controls' the degradation rate and consequently the cycling life. A more beneficial NoC factor can be obtained by either procuring better batteries or consistently use lower C-rates.

5.2. Market uncertainty

The research regarding applications of 2nd life batteries is rapid and many organisations are looking in to investing in the batteries' 2nd life. This could potentially lead to more participants on the balancing markets, which will lead to lower market prices as the market saturates.

A small sensitivity analysis was performed as presented in section 4.2.5. The result of the analysis clearly shows that the model is sensitive for lower market prices. The analysis was done by dividing all market prices by two. The factor two might simulate a too aggressive price fluctuation, but as the result showed decreased earnings by a factor of four. This topic is in need of further investigation. To draw any relevant conclusion, market simulations would be needed, in conjunction with statistical models which could provide probabilities of a certain case becoming reality.

The political climate is an area outside the scope of this thesis. However, it is important to remember that politics can widely affect the markets which BESS' can trade on by e.g. introducing market regulations.

5.3. Business Case - Battery cost allocation

Apart from the insights mentioned above, the thesis generated an understanding of a business case regarding battery cost allocation. However, the developed MATLAB model does not accommodate those types of calculations and therefore, a simple reasoning and discussion provided below will suffice to explain the gained insights.

As mentioned in section 2.1, the freight industry is subject for low profit margins. This means that the participants on freight market face the same earning potentials, and the largest revenue goes to the company which is good at cost minimization. The mark-up is higher for sustainable road freight, but still, from a business point of view, there is more to wish for. For a freight company, only operating trucks, this might be the entire reality regarding the earning potential. However, for freight companies which commit to

2nd life battery applications, the business model could be manipulated and adjusted into something different.

Imagine a case where the freight company's TCO sums up to 100 euros per day, including battery degradation costs. Then imagine a market which is willing to pay 102 euros per day for a TaaS (transport as a service). This essentially entails that 2 euros can be made that day. The new business case occurs when the TCO can be pushed to lower levels than 100 euros per day.

The TCO is an internal affair, meaning that a company calculates its own total costs. Usually, the TCO should be quite homogeneous for a saturated market, which also ebbs out in the low market mark-ups. But what if the company decides to exclude battery degradation from the TCO, resulting in a TCO of perhaps 97 euros per day, instead of the previously mentioned 100 euros per day. This would essentially mean that the company could provide the market with lower bids (including mark-up), say 100 euros per day. The total earnings would increase (3 instead of 2 euros per day) and simultaneously, a larger share of the market could be taken as the company offers a cheaper TaaS.

Of course, costs cannot disappear in thin air, they need to be accounted for somewhere. That is where the 2nd life batteries become important. For a company with a 2nd life battery segment, some of the battery cost could be allocated to the 2nd life. During the 2nd life, the earnings are larger per cycled kWh in comparison to the 1st life, as shown in e.g. figures 4.3 and 4.7. This means that the the two connected lines (1st respectively 2nd life) in figures 4.3 and 4.7 could be leveled out and have the same slope, resulting in a steady cashflow over time by decreasing the cost in 1st life and increasing the costs in the 2nd life. The total cost would remain the same, but the revenue in the 1st life would increase both in actually monetary flow terms, but also in terms of a larger market share.

This insight was gained by observing figures 4.3 and 4.7, which clearly raises the questions whether or not to invest in electric vehicles, as the batteries are more profitable as stationary applications. However, the society needs electric transport. There is no way around that as traditional combustion engines pollute the environment. The electric vehicles are here to stay, the question is how to use the batteries in order to generate the largest overall value, both in economic and environmental measures.

5.4. Further Research

5.4.1. Model improvements and test cases

There are many refinements of the model that would be interesting to implement. A first step could be updating the trading algorithm to a non-greedy one and optimizing for an entire day, instead of hour by hour. This should entail higher total earnings and a more intelligent usage of the available battery capacity.

The trading algorithm could also take on a different character and change into a machine learning one. The algorithm could then possibly react to market signals, trade accordingly and actually trade not knowing all market data, but trade in line with statistics. This would lead to more reliable results and an algorithm that could actually be applied in a real trading situation.

5.4.2. Adaptive trade size

An additional improvement of the model ought to be made in order to maximize profit. When studying the results presented in figure 4.1 and 4.4, it is evident that more trades are blocked as the battery size shrinks over time, due to degradation.

When the model runs, it completes the entire life with one, pre-decided, trade size. This means that the same trade size will be a larger share of the BESS size as time goes by, since the BESS size is decreasing. Consequently, more trades will be blocked as the probability of trading outside the battery size, i.e $SoC < 0$ or $SOC > 100$, increases.

This might not at first seem like an issue. However, the issue arises due to the nature of trading algorithm.

The trading algorithm is constructed by several if-statements which acts as logical gates and helps the algorithm choose which trade that should take place. There are different set of rules for different trades. However, for all trade types, one of the criterion is $0 < SOC_{after\ trade} < 100$. This means that the algorithm will occasionally 'miss' trading as all of the rules for a certain trade event is not fulfilled. This could be avoided by using an adaptive trade size.

An adaptive trade size refers to the procedure of updating the trade size if the algorithm blocks trade for an entire hour, due to the trading rules. Essentially, a boolean 'flag' could be used to keep track if trade occurred and if no trade was identified, the trade size would be updated by $TradeSize_{new} = TradeSize_{old} - 0.1MW$. This procedure would be iterated until $TradeSize_{new} = 0.1$. Consequently, more trade events would take place as the trade size would more often pass the SoC-requirement, and as a result, the total earnings over time would increase.

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Appendix A.

Rainflow Counting Algorithm

The rainflow algorithm is a counting algorithm, commonly used in fatigue analysis which facilitates the identification, quantification and counting of half and full cycles, i.e. how several smaller strains can be added together, and equal one larger strain. This can be applied to battery degradation, as the SOC-data can be interpreted as the load history.

The standard implementation of the algorithm contains the following steps.

- Hysteresis filtering
- Peak-valley filtering
- Discretization
- Four point counting method

Hysteresis filtering is implemented in order to remove very shallow cycles contributing to negligible wear.

This is achieved by implementing a gate which filters out cycles with amplitudes smaller than the gate. The result of this is showed in figure A.1

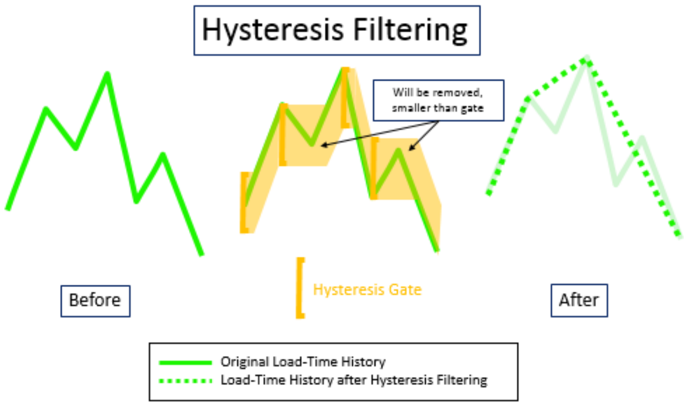


Figure A.1.: Schematics over how hysteresis filtering affects load history. [44]

The aim of **peak-valley filtering** is to remove cycles which do not contribute to any fatigue. These are intermediate data points within a larger cycle and are therefore removed in accordance to figure A.2.

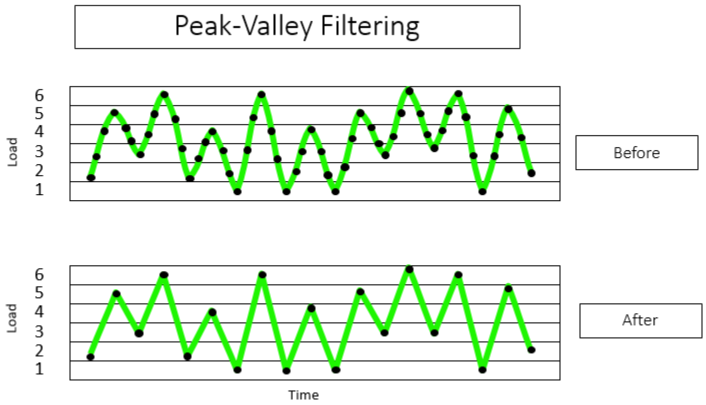


Figure A.2.: Illustrative description over how peak-valley filtering affects load history. [44]

The **discretization** divides the y-axis (amplitudes) into discrete values and adjusts each data point to the closest discrete value. In figure A.3, there are six discrete values to which each amplitude is allocated to.

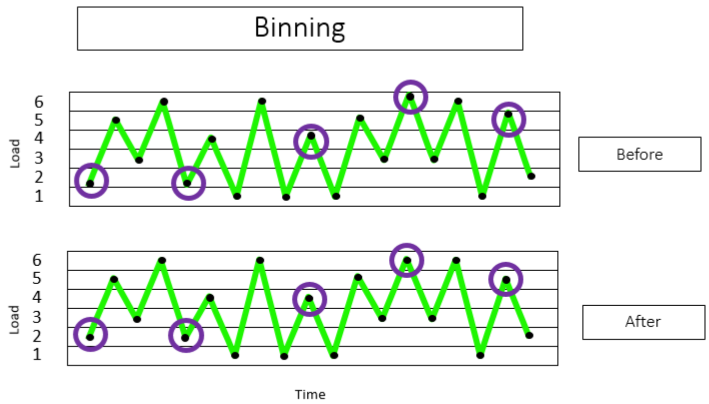


Figure A.3.: Illustrative description over how discretization affects load history. [44]

The final stage of the rainflow algorithm is the **four point counting method**, which follows the subsequent steps.

Four consecutive point P1, P2, P3, P4 (from left to right) are identified as shown in figure A.4. The inner stress is defined as $|P2 - P3|$ and the outer as $|P1 - P4|$. If the inner range is bound by the outer range, one cycle is counted. Therefore, in figure A.4 one cycle is added to the rainflow matrix. If the opposite applies, the cycle is not counted.

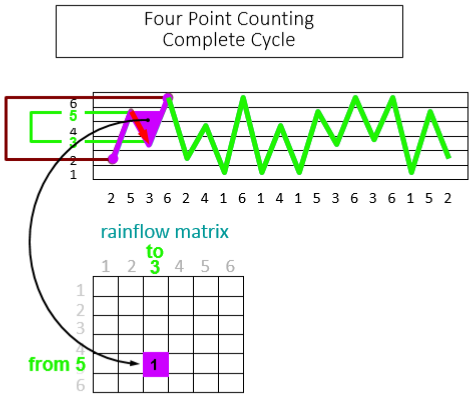
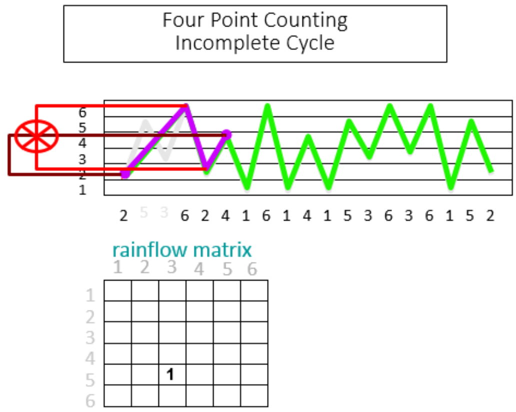
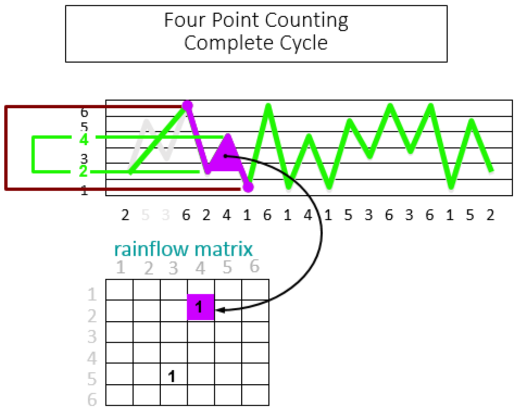


Figure A.4.: Illustrative figure of the four point method. [44]

Thereafter, the inner points P2 and P3 are removed and four new consecutive point are identified, where P1 remains the same, P2 takes on the value of the previous P4 and P3 and P4 are the next identified turning points. In the case of figure A.5a, the inner range is not bounded by the outer, meaning that the cycle is not counted. When this occurs, the points will all move one step to the right, as shown in figure A.5b. This process is iterated until all complete cycles are removed.



(a) Illustrative figure over an incomplete cycle using the four point counting method.



(b) Illustrative figure over complete cycle following an incomplete cycle.

Figure A.5.: Figure showing how the rainflow algorithm approaches incomplete cycles.

To conclude, the information that the rainflow counting algorithm preserves are number of cycles, range of cycles and the mean of cycles which provides all necessary information to calculate battery degradation in accordance with algorithm 1.

Appendix B.

Results, all combinations

B.1. Vehicle A

NoC factor 1, cal. life 10 years, threshold 40-60%

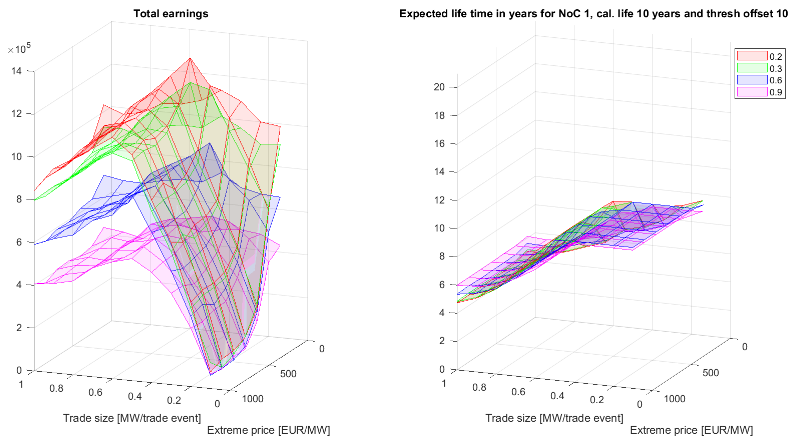


Figure B.1.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 40-60%.

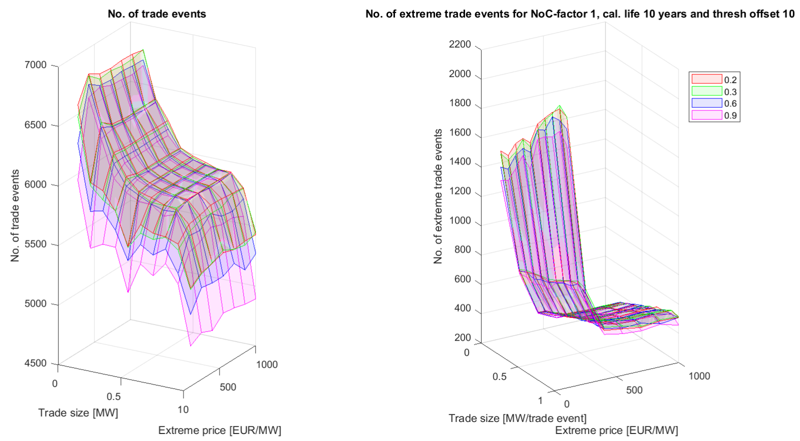


Figure B.2.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 40-60%.

NoC factor 1, cal. life 10 years, threshold 30-70%

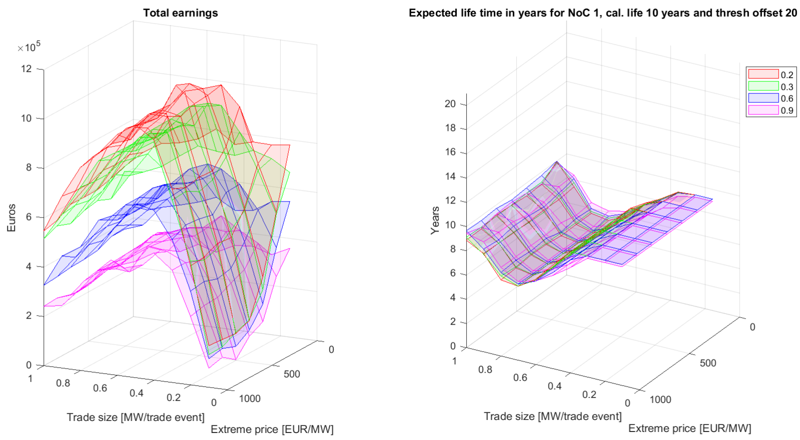


Figure B.3.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%.

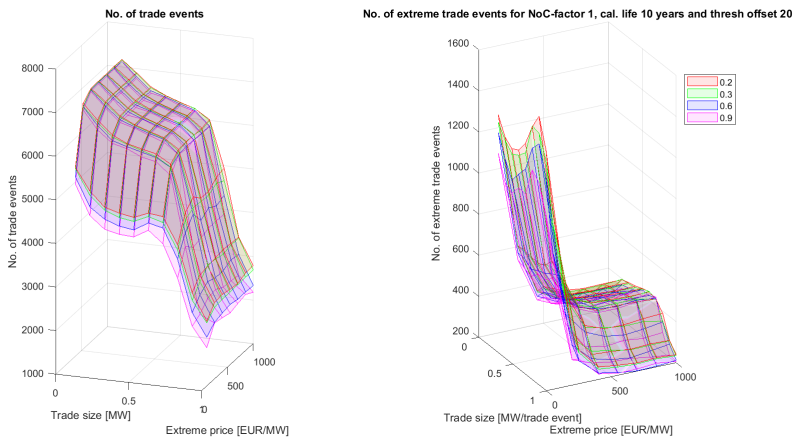


Figure B.4.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%.

NoC factor 1, cal. life 20 years, threshold 40-60%

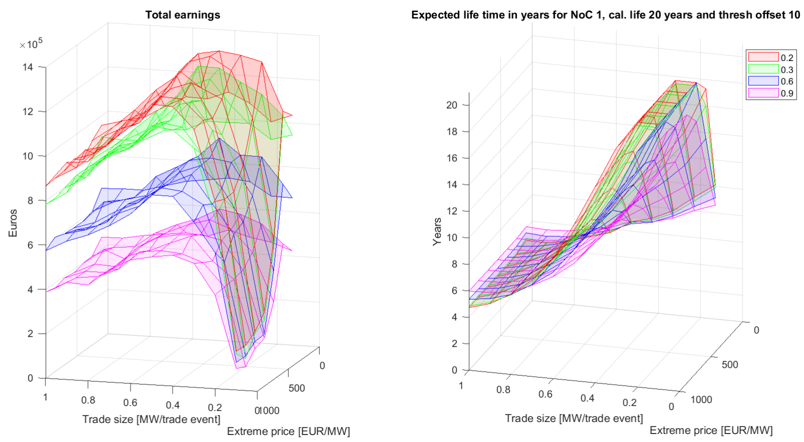


Figure B.5.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 40-60%.

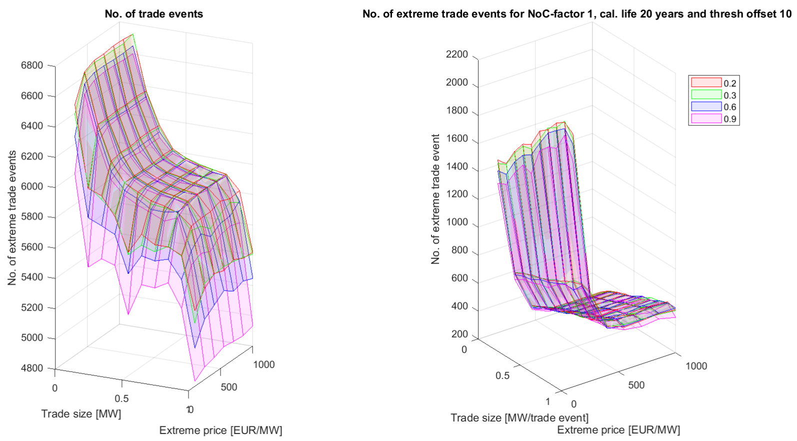


Figure B.6.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 40-60%.

NoC factor 1, cal. life 20 years, threshold 30-70%

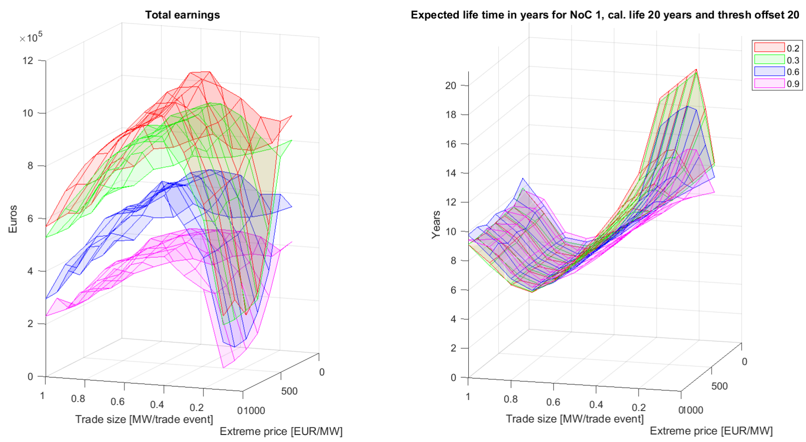


Figure B.7.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%.

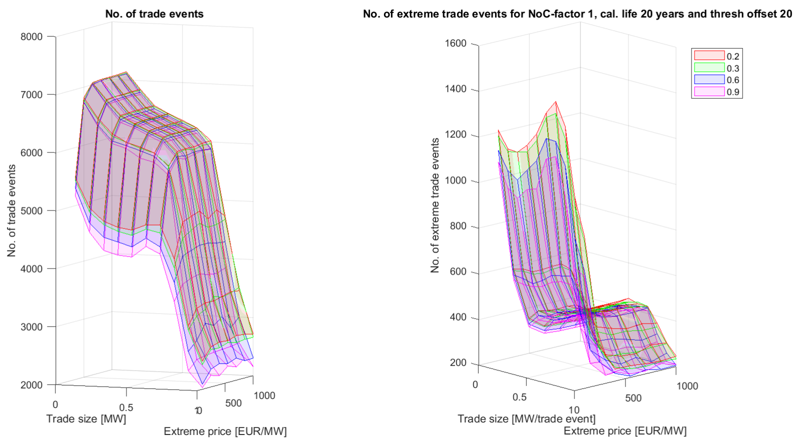


Figure B.8.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%.

NoC factor 2, cal. life 10 years, threshold 40-60%

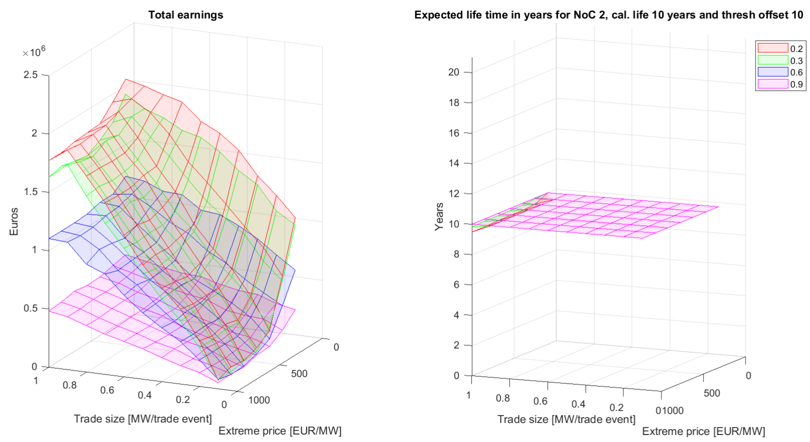


Figure B.9.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 40-60%.

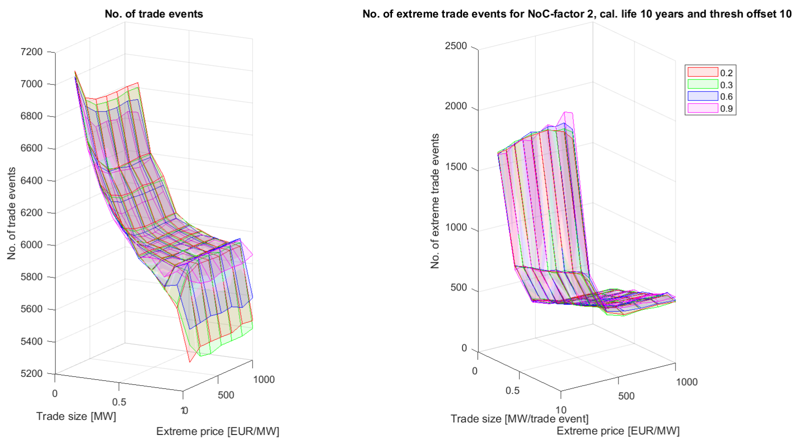


Figure B.10.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 40-60%.

NoC factor 2, cal. life 10 years, threshold 30-70%

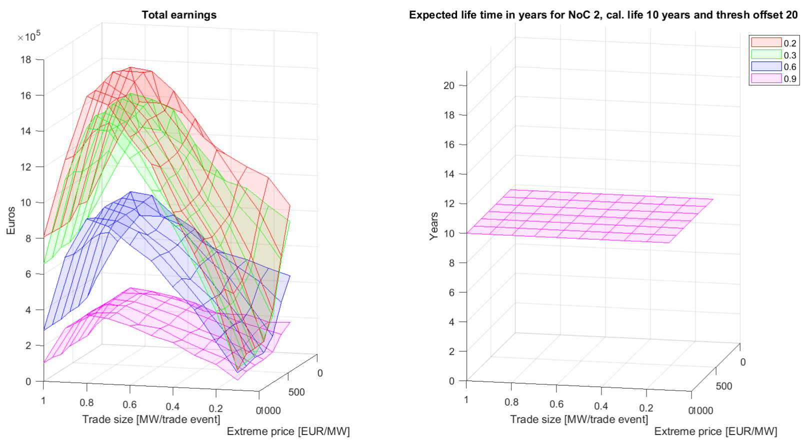


Figure B.11.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 30-70%.

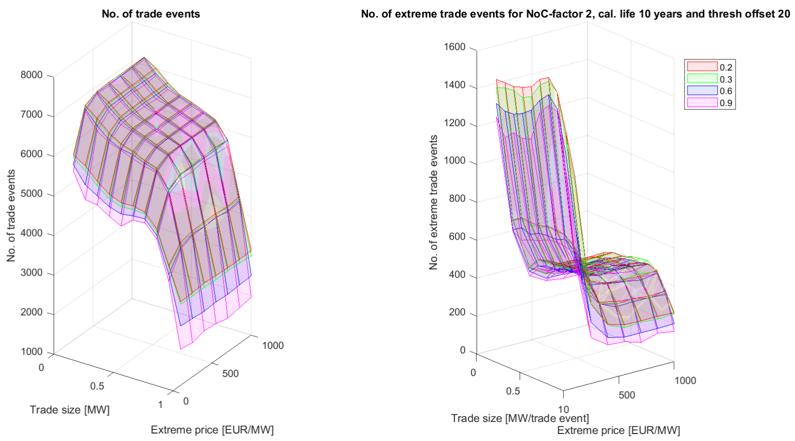


Figure B.12.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 30-70%.

NoC factor 2, cal. life 20 years, threshold 40-60%

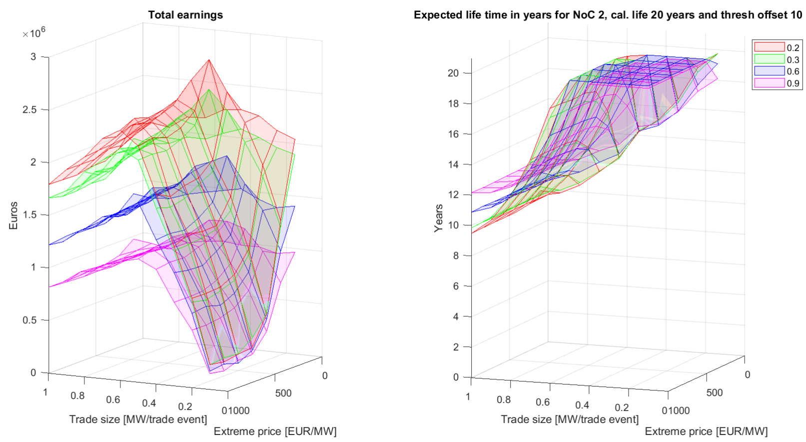


Figure B.13.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 40-60%.

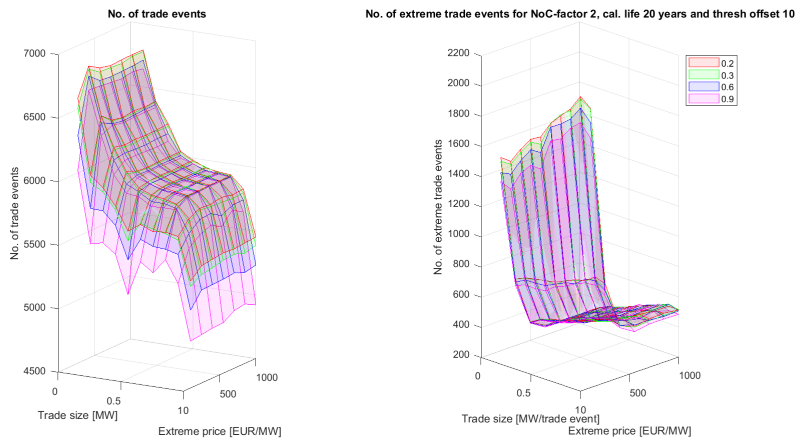


Figure B.14.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 40-60%.

NoC factor 2, cal. life 20 years, threshold 30-70%

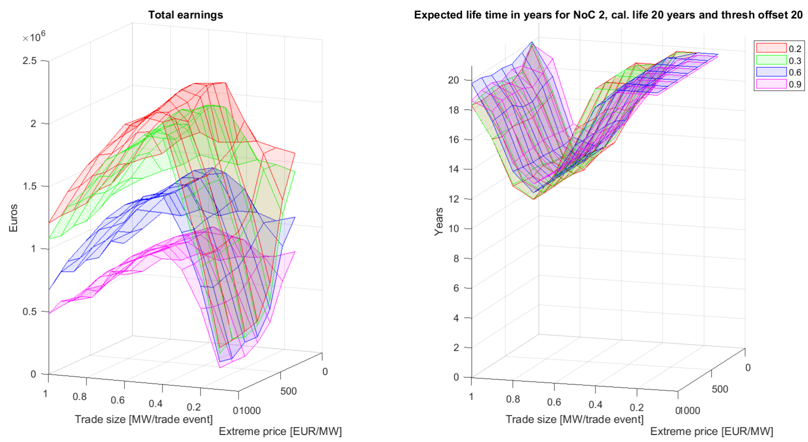


Figure B.15.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%.

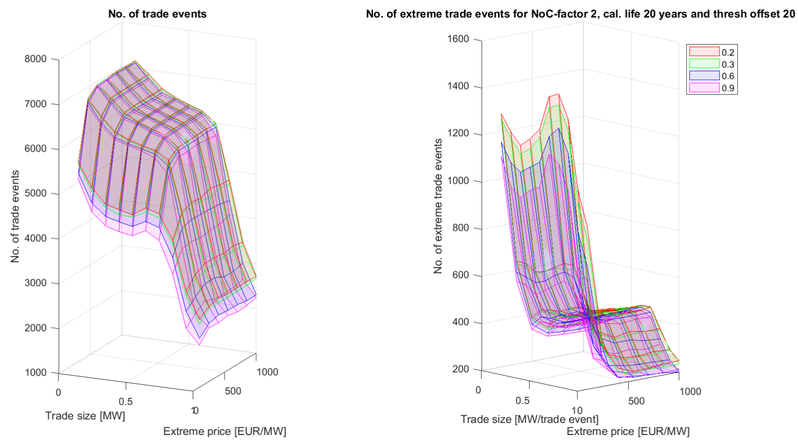


Figure B.16.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%.

NoC factor 6, cal. life 10 years, threshold 40-60%

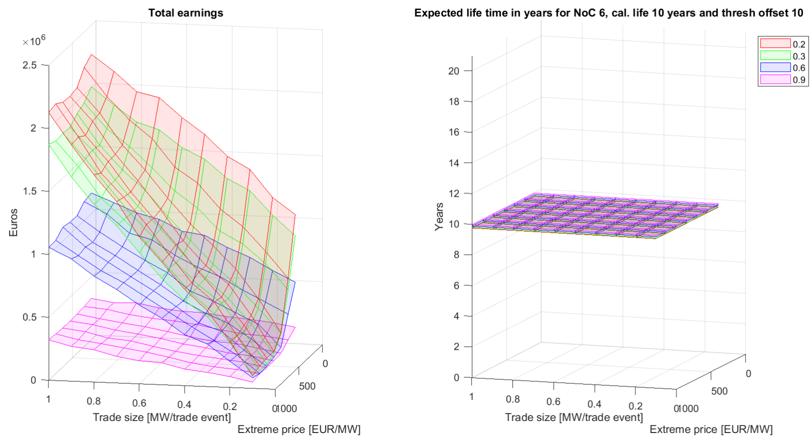


Figure B.17.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 40-60%.

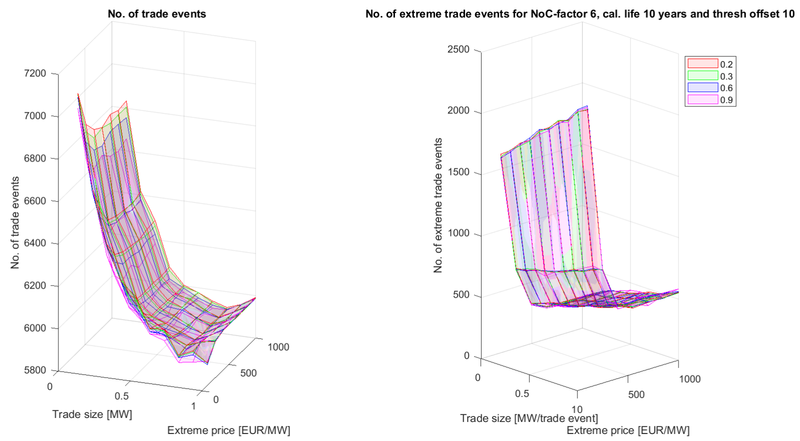


Figure B.18.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 40-60%.

NoC factor 6, cal. life 10 years, threshold 30-70%

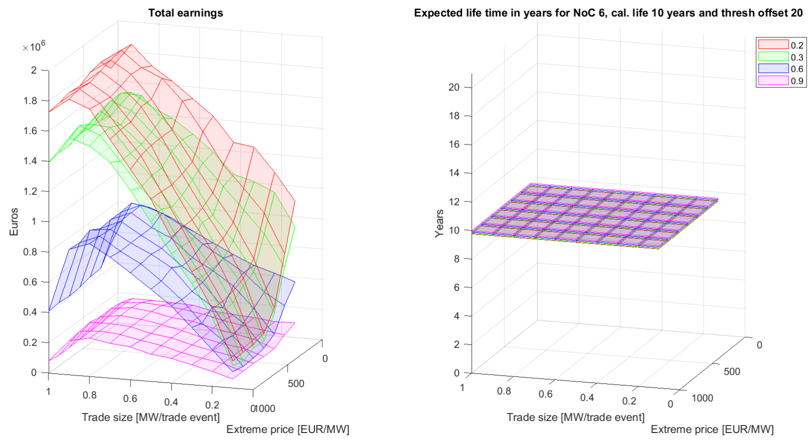


Figure B.19.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 30-70%.

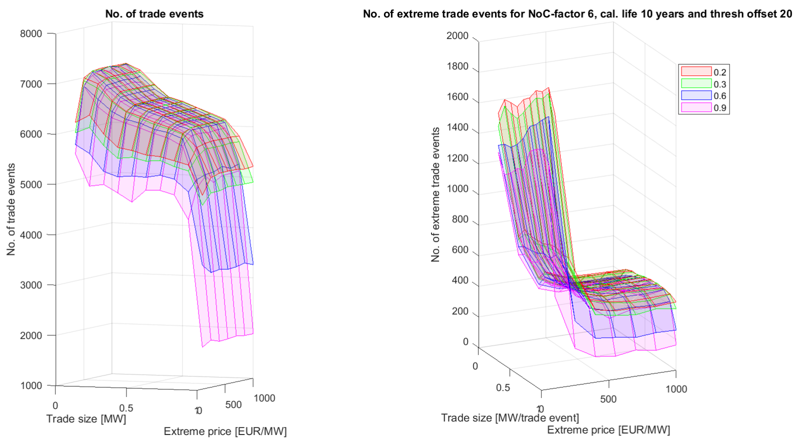


Figure B.20.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 30-70%.

NoC factor 6, cal. life 20 years, threshold 40-60%

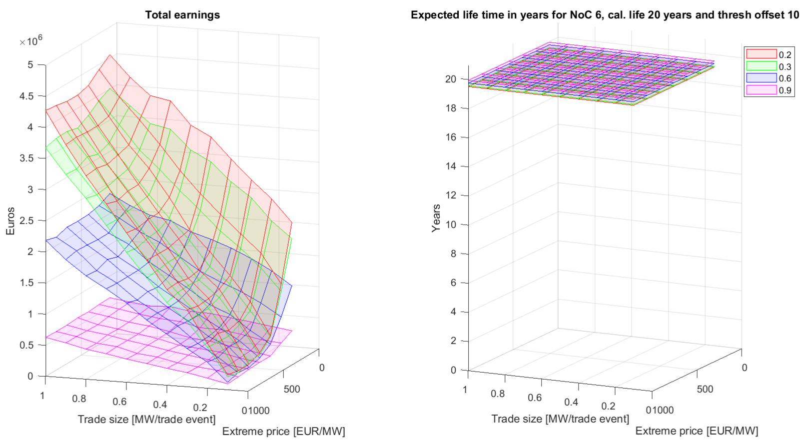


Figure B.21.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%.

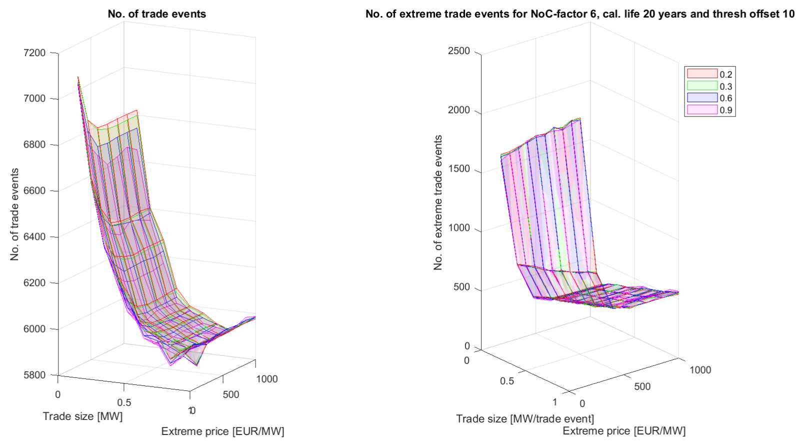


Figure B.22.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%.

NoC factor 6, cal. life 20 years, threshold 30-70%

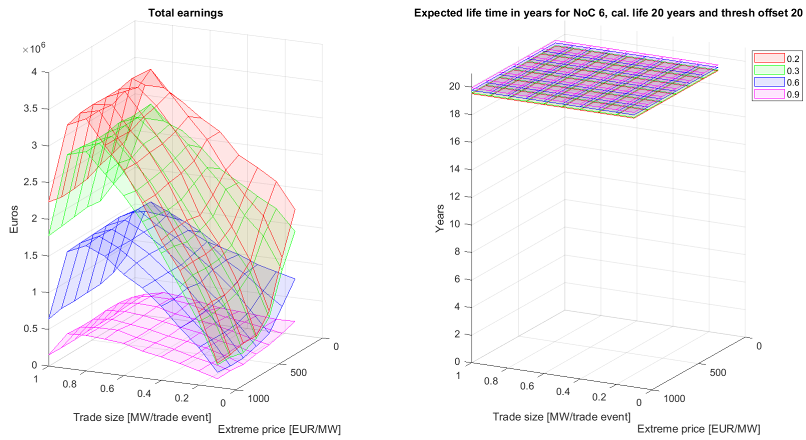


Figure B.23.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%.

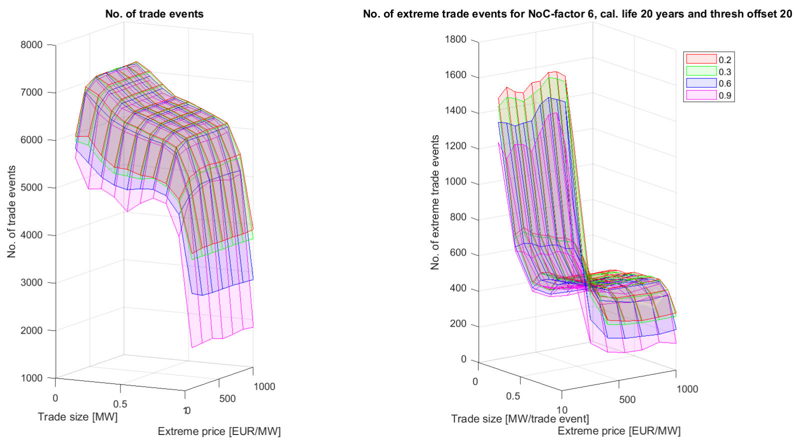


Figure B.24.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%.

B.2. Vehicle B

NoC factor 1, cal. life 10 years, threshold 40-60%

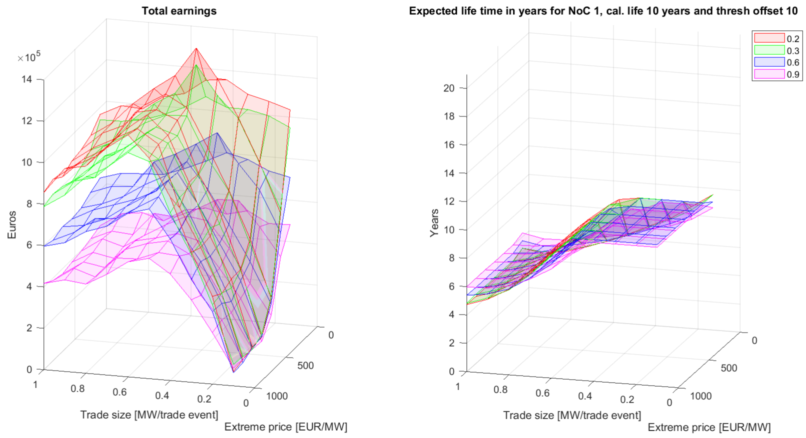


Figure B.25.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 40-60%.

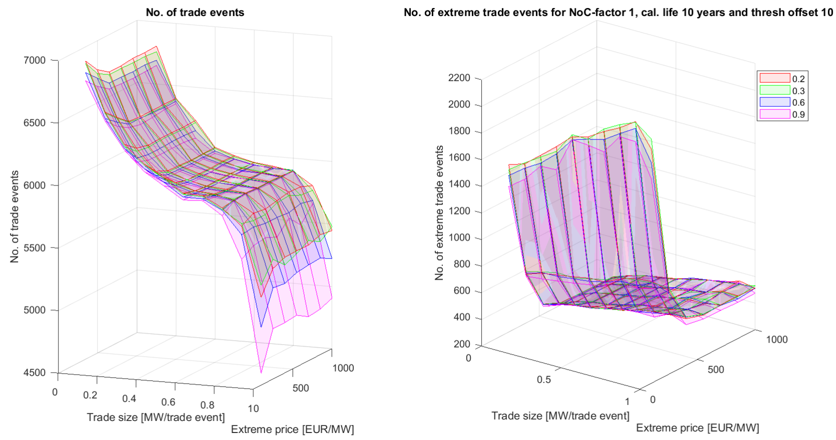


Figure B.26.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 40-60%.

NoC factor 1, cal. life 10 years, threshold 30-70%

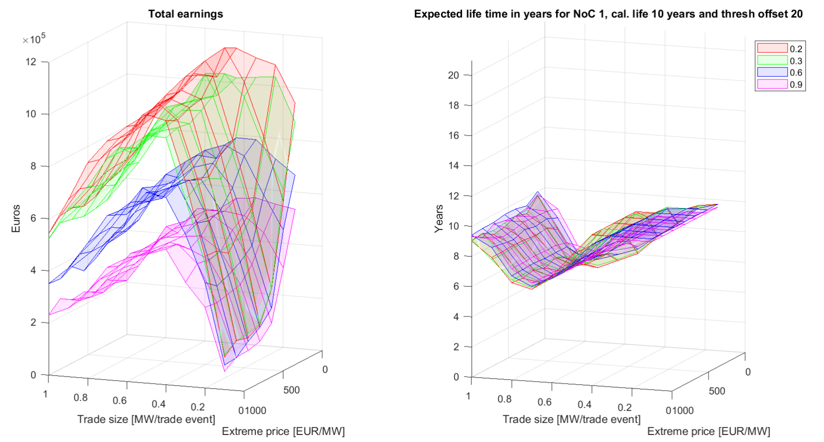


Figure B.27.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%.

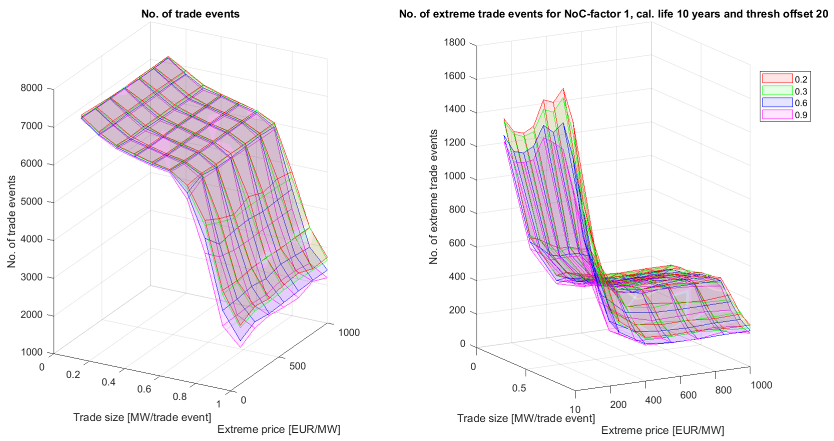


Figure B.28.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 10 years and a threshold between 30-70%.

NoC factor 1, cal. life 20 years, threshold 40-60%

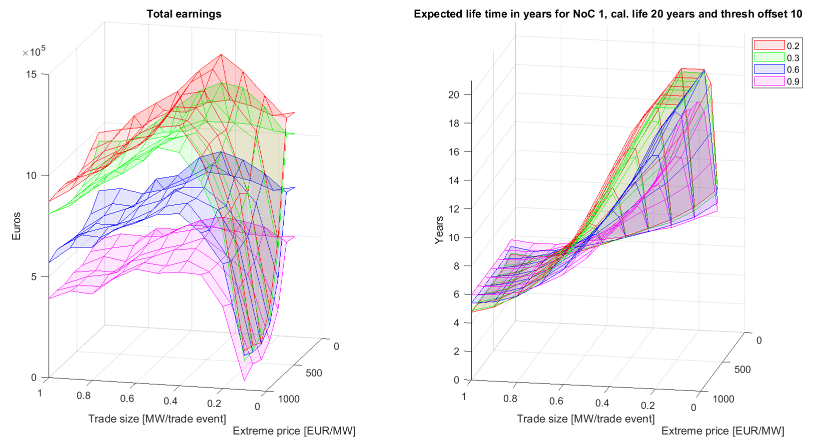


Figure B.29.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 40-60%.

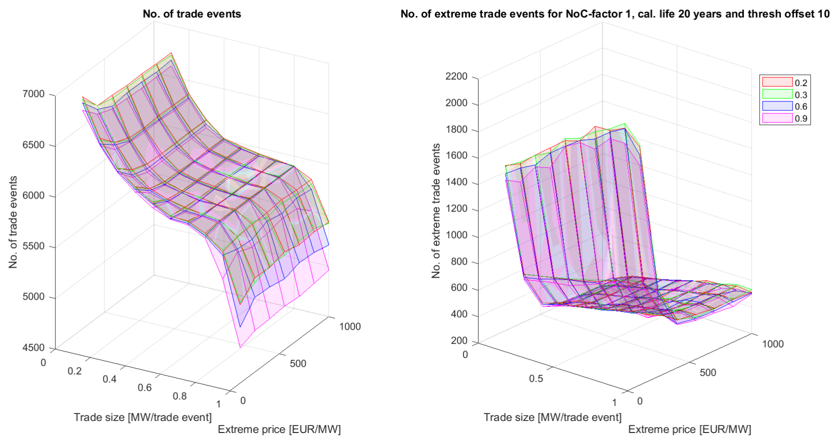


Figure B.30.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 40-60%.

NoC factor 1, cal. life 20 years, threshold 30-70%

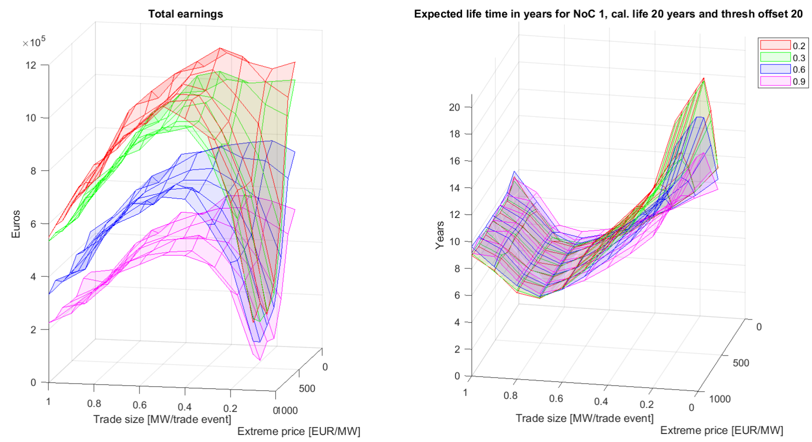


Figure B.31.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%.

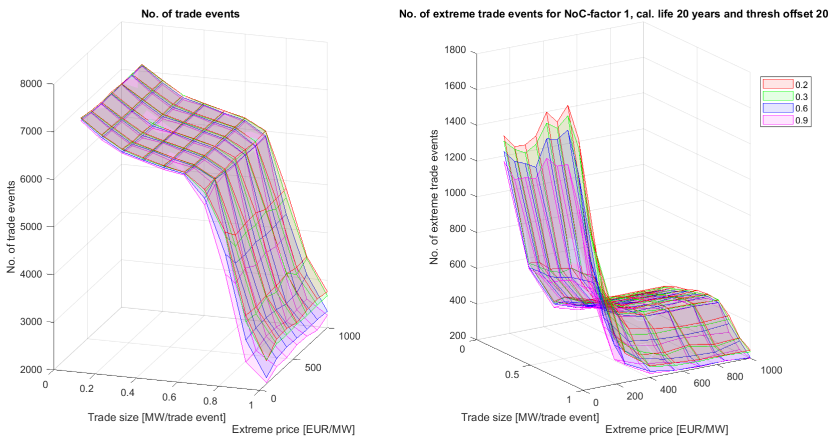


Figure B.32.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 1, calendar life of 20 years and a threshold between 30-70%.

NoC factor 2, cal. life 10 years, threshold 40-60%

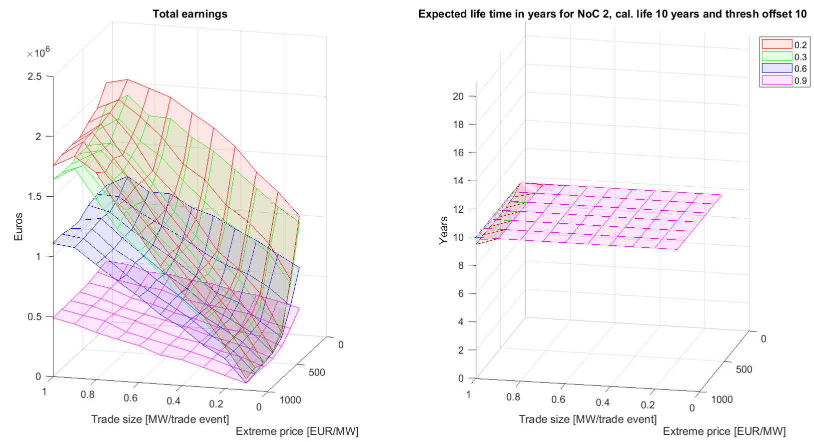


Figure B.33.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 40-60%.

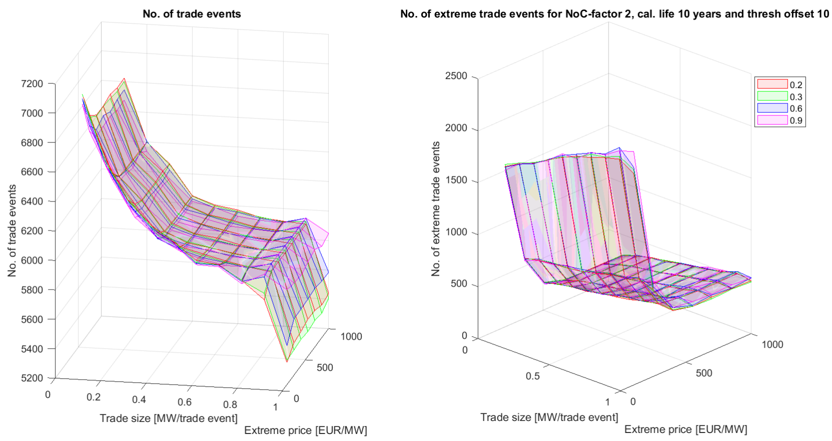


Figure B.34.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 40-60%.

NoC factor 2, cal. life 10 years, threshold 30-70%

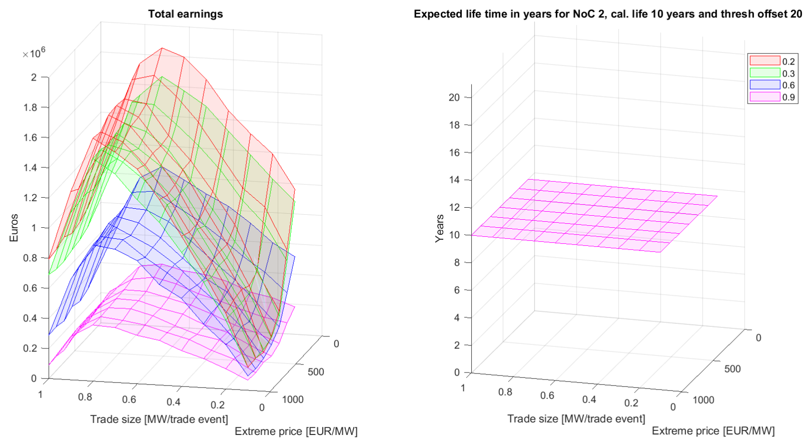


Figure B.35.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 30-70%.

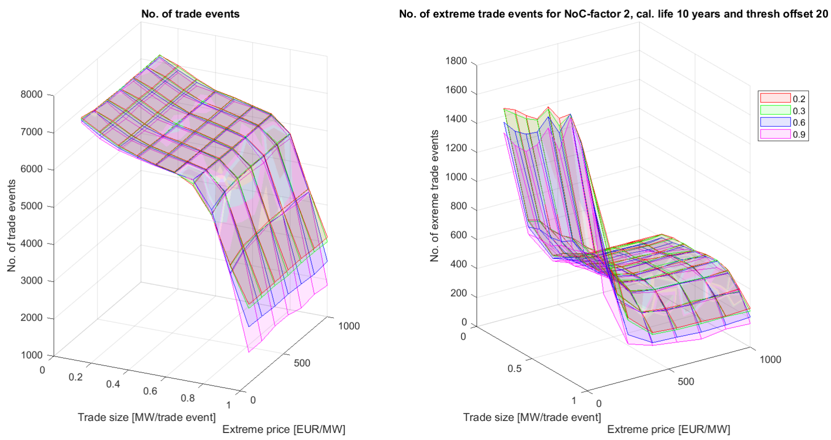


Figure B.36.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 10 years and a threshold between 30-70%.

NoC factor 2, cal. life 20 years, threshold 40-60%

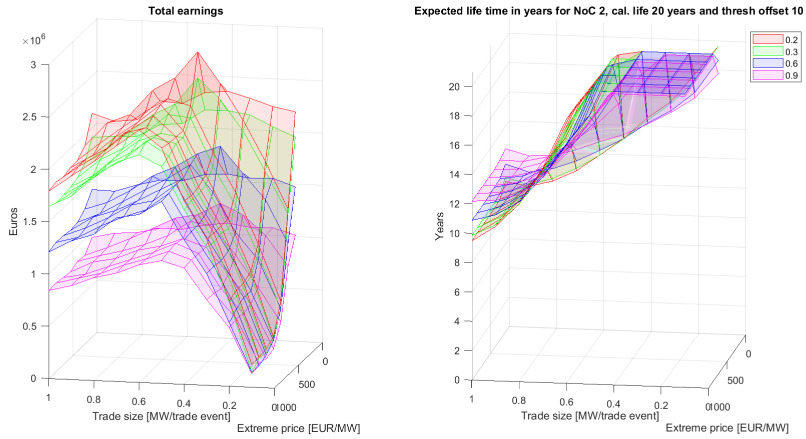


Figure B.37.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 40-60%.

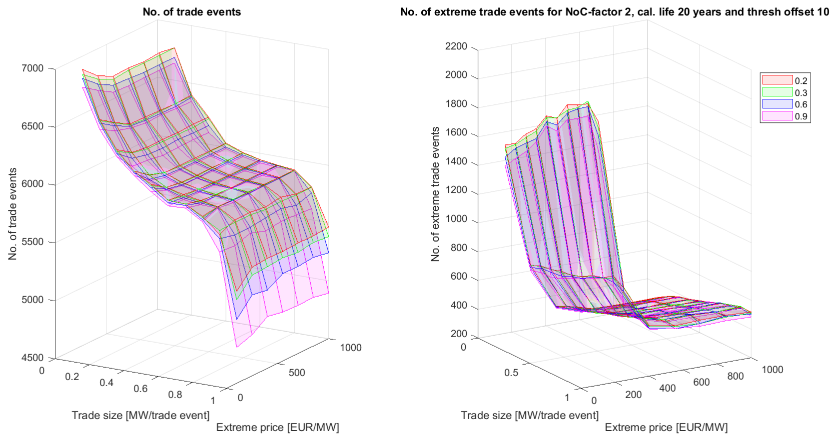


Figure B.38.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 40-60%.

NoC factor 2, cal. life 20 years, threshold 30-70%

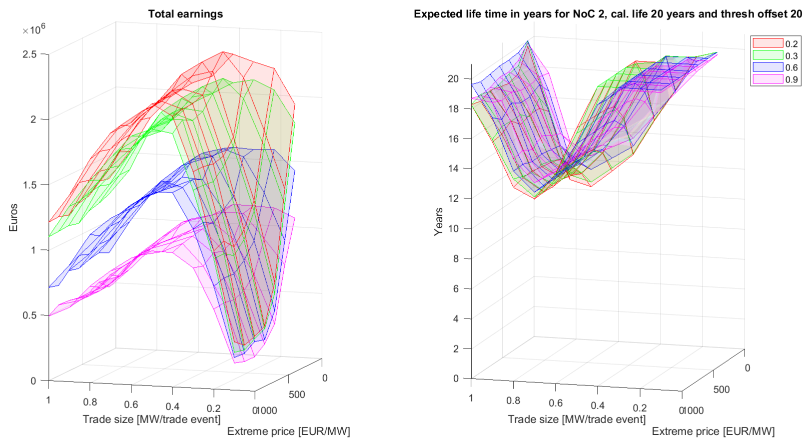


Figure B.39.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%.

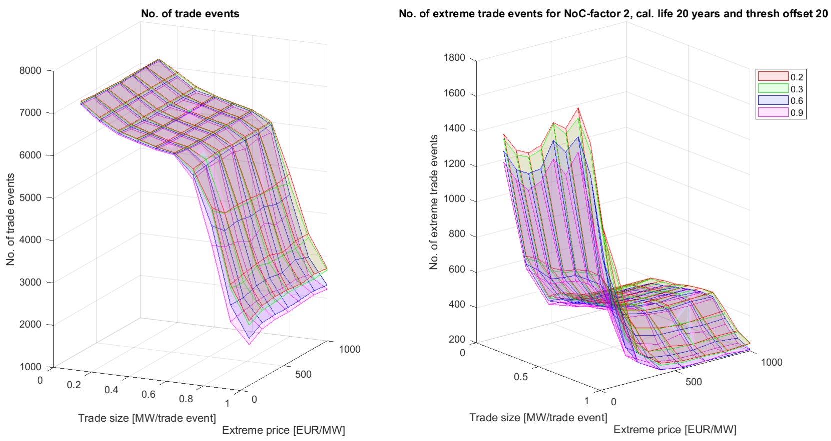


Figure B.40.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 2, calendar life of 20 years and a threshold between 30-70%.

NoC factor 6, cal. life 10 years, threshold 40-60%

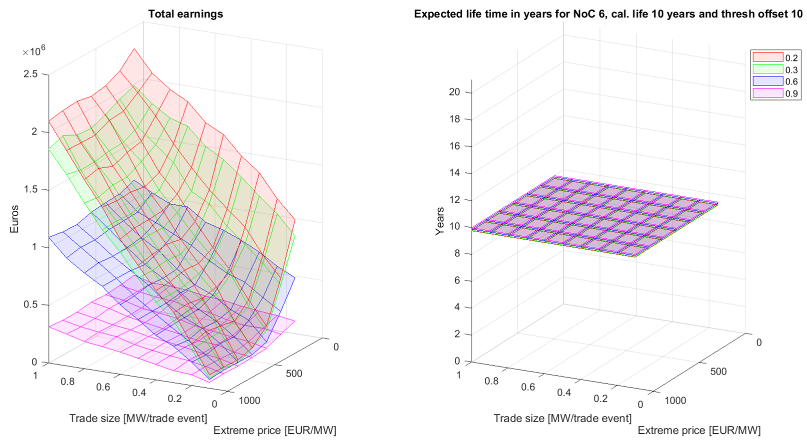


Figure B.41.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 40-60%.

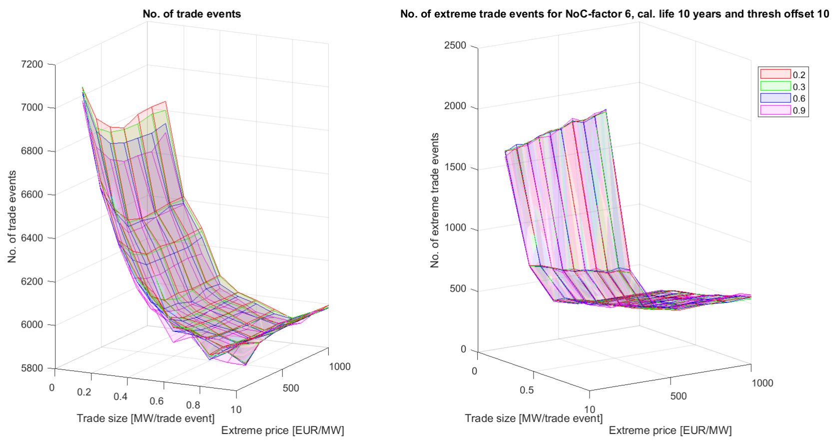


Figure B.42.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 40-60%.

NoC factor 6, cal. life 10 years, threshold 30-70%

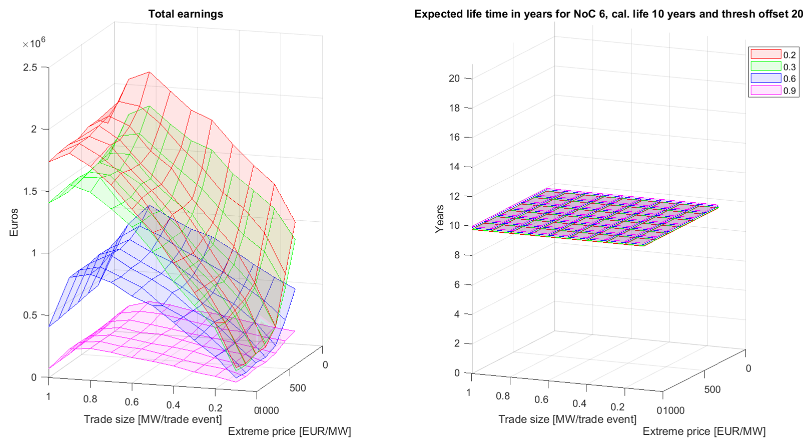


Figure B.43.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 30-70%.

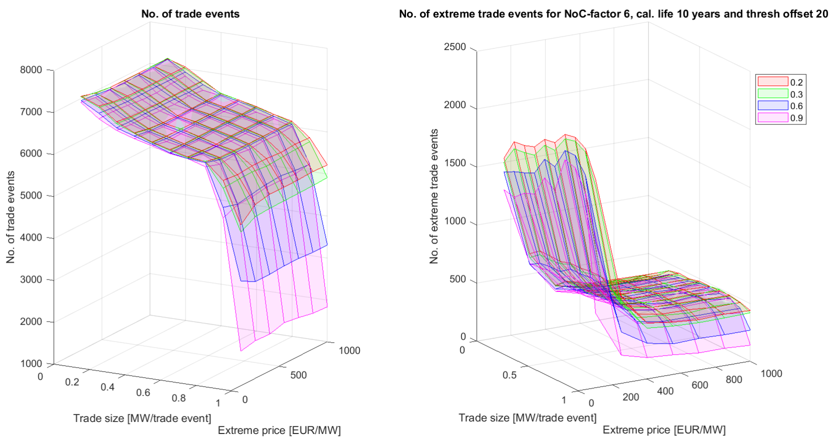


Figure B.44.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 10 years and a threshold between 30-70%.

NoC factor 6, cal. life 20 years, threshold 40-60%

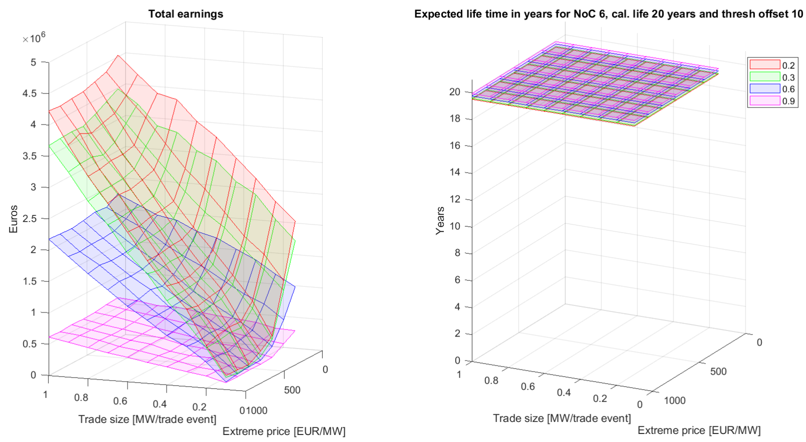


Figure B.45.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%.

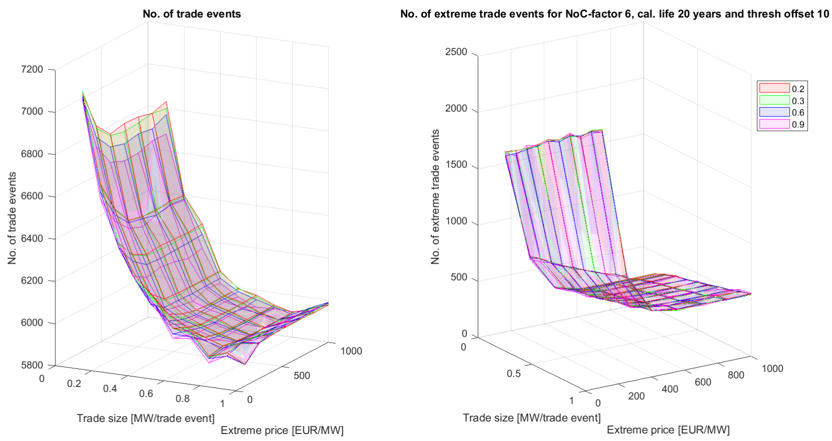


Figure B.46.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 40-60%.

NoC factor 6, cal. life 20 years, threshold 30-70%

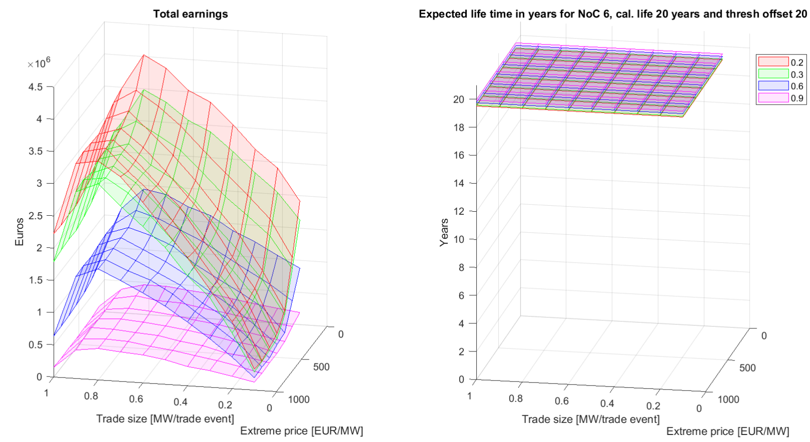


Figure B.47.: Figures displaying total earnings and expected life time for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%.

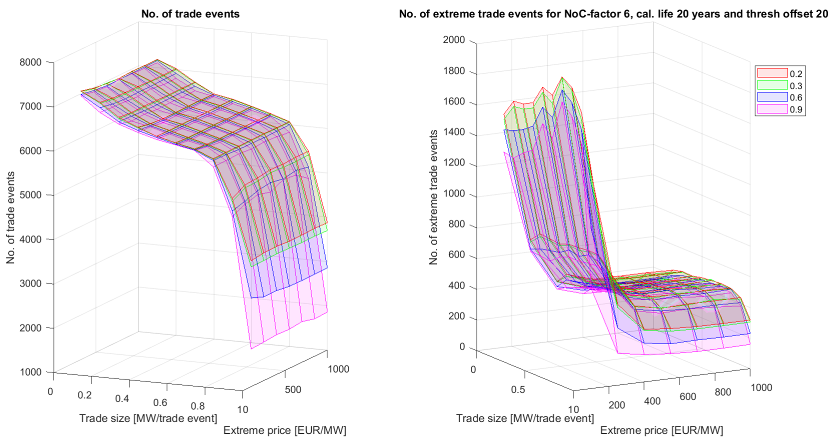


Figure B.48.: Figures displaying the normalized number of trade events and number of extreme trade events for different combinations of trade size and extreme price, with a NoC factor of 6, calendar life of 20 years and a threshold between 30-70%.